

Advances in Volcanology

Zack Spica
Corentin Caudron *Editors*

Modern Volcano Monitoring



 Springer

Advances in Volcanology

An Official Book Series of the International
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ISSN 2364-3277

ISSN 2364-3285 (electronic)

Advances in Volcanology

ISBN 978-3-031-86840-5

ISBN 978-3-031-86841-2 (eBook)

<https://doi.org/10.1007/978-3-031-86841-2>

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Introduction

Volcanoes are among the most powerful and unpredictable natural phenomena on Earth, capable of reshaping landscapes and disrupting communities in an instant. To mitigate the risks posed by eruptions, scientists have developed advanced monitoring techniques that provide critical early warnings and improve our understanding of volcanic activity.

Modern volcano monitoring nowadays combines cutting-edge technology, such as satellite imagery, telecommunication optical fibers, and artificial intelligence, with traditional field observations to track key indicators like seismic activity, ground deformation, and gas emissions. These methods allow researchers to detect subtle changes that may signal an impending eruption, helping to protect lives and infrastructure. As technology continues to evolve, volcano monitoring is becoming more accurate and accessible, enhancing global preparedness for volcanic hazards. Yet, several challenges remain.

As volcanology is a complex science at the interface between geology, geochemistry, and geophysics, a global understanding of many of these aspects is essential to embrace the diversity of a volcanic system. Compared to books discussing how volcanoes work, the different volcanic processes (eruption types, volcano types, etc.), or describing a particular major eruption, this book focuses on how scientists monitor volcanoes. It describes the different tools developed during the last decades and in which direction volcanological monitoring is going. We present the most recent advances in the field ranging from muons to more traditional approaches such as gas geochemistry in fumaroles. Unfortunately, the book does not cover the ground deformation due to unforeseen circumstances. The readers are referred to other publications if they want to gather further information on this topic. Modern volcano monitoring will offer a hands-on experience directly useful for the reader who wants to start applying the principles exposed.

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Time-Variable Volcano Gravimetry

Daniele Carbone

Abstract

Among the geophysical techniques used to monitor volcanic unrest, only gravimetry can supply direct information on changes in the distribution of underground mass over time and can thus provide unique insight into processes such as magma accumulation in void space or gas segregation at shallow depths. Despite its great potential, time-variable volcano gravimetry is not widely adopted, mainly due to (i) the high cost of instrumentation and (ii) the challenge in assessing the relatively small volcano-related gravity changes against unfavorable environmental conditions. Nonetheless, past studies have highlighted the value of time-lapse and continuous gravity observation for characterizing hazards, as well as improving our understanding of how volcanoes work. In this chapter a comprehensive technical, methodological and scientific insight is provided into time-variable volcano gravimetry, highlighting the advantages and limits of the method, as well as the future directions which could broaden its application.

1 Introduction

Most phenomena underlying volcanic activity involve underground mass redistribution and can thus induce gravity changes measurable at the surface. Indeed, gravimetry is the only method providing direct information on underground mass changes over time (Van Camp et al. 2017) and can therefore be utilized to gain unique insight into the mechanisms behind volcanic unrest (Brown and Rymer 1991; Battaglia et al. 2008; Carbone et al. 2017). Past studies from several volcanoes worldwide have shown that time-variable gravity changes with amplitudes between a few and several hundred μGal ($1 \mu\text{Gal} = 10^{-8} \text{ m/s}^2$) may develop before, during and after eruptive events, over time scales ranging from hours to years (Eggers 1983; Rymer et al. 1993; Battaglia et al. 1999; Jousset et al. 2003; Gottsmann et al. 2007; Bonvalot et al. 2008; Bagnardi et al. 2014; Carbone et al. 2015; Poland et al. 2021). In most cases, time gravity changes at active volcanoes occur in conjunction with ground deformation and the joint analysis of the two quantities allows to obtain information on the source mechanism which could not be achieved if only one dataset was available (de Zeeuw-van Dalfsen et al. 2005; Battaglia and Hill 2009; Chauhan et al. 2020; Pulvirenti et al. 2021). Under other circumstances, mass change may represent the only insight that can be used to constrain processes occurring in the

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subsurface, like when magma accumulates in pre-existing void space (Rymer et al. 1993), or when a magma body undergoes an overall density change at constant volume (Bagnardi et al. 2014). In those cases, gravity may become crucial to defining the state of activity of a volcano and characterizing hazards.

In this chapter, I provide a comprehensive review of the instrumentation and methodologies used to characterize gravity change at volcanoes, as well as the factors that have limited the application of gravimetry to monitor and study active volcanoes, including the high cost of gravimeters and their general unsuitability for use under harsh environmental conditions. Also discussed are current and future developments, which are meant to address the above limitations, toward a full exploitation of time-variable volcano gravimetry.

It is worth mentioning that the focus here is on time-varying gravimetry at volcanoes and the possible use of gravity measurements to image the underground density structure (static gravimetry) is not discussed throughout this chapter. The interested reader can refer to the papers by Schiavone and Loddo (2007) and Saxby et al. (2016) for more information on this topic.

2 Measuring Time-Varying Gravity at Active Volcanoes

It is now well established that the bulk processes which control volcanic activity can induce time gravity changes measurable at the ground surface (Battaglia et al. 2008; Williams-Jones et al. 2008; Carbone et al. 2017). Past studies have shown that the amplitude of these changes usually ranges between a few and a few hundreds of μGal . Hence, applying gravimetry to monitor and study active volcanoes requires detection of variations over time as small as one part in 10^6 to one part in 10^8 of the standard gravity acceleration on Earth ($g = 9.8 \text{ m/s}^2$).

Very high precision instruments (namely, the gravimeters) are required to measure such tiny changes and a great care must also be taken to ensure that the measurements are suitably

performed and that the non-volcanic effects are properly removed from the gravity signal.

2.1 The Gravimeters

The gravimeters measure the vertical component of gravity and come in two main types, relative and absolute. Relative gravimeters can only measure changes of the gravity acceleration, in both space, i.e., between two different measurement sites, and time, i.e., at a fixed site, during the period from an arbitrary starting time. Conversely, absolute gravimeters give direct access to the actual value of the gravitational acceleration, g , at the installation site.

2.1.1 Relative Gravimeters

Spring Gravimeters

In general, commercially available relative gravimeters operate by measuring the change in displacement of a suspended proof mass. Spring gravimeters are the most widely used devices for volcano gravimetry, since they are small and compact, hence easily transportable, and do not take much power to work, meaning that they can run on batteries for extended periods of time, and can thus be operated at remote sites where mains electricity is not available. Spring gravimeters measure the change in the equilibrium position of a proof mass suspended from a spring, which results from a change in the gravity field. To achieve the precision required for measuring volcano-related gravity changes, different strategies have been adopted by various instrument manufacturing companies. One of the most successful designs was developed by LaCoste & Romberg (L & R) in 1939 and is based on the inclined zero-length spring assembly (LaCoste and Romberg 2004). A zero-length spring is pre-stressed and wound in such a way that, when no mass is applied, it behaves as though it has no physical length. In L & R instruments, the zero-length spring is attached to the center of a pivoting beam, holding the proof mass at its outside end (Torge 1989). An increase in the mechanical sensitivity

is achieved by designing the system so that the torque characteristics of gravity and spring forces are very close to each-other (astatization). Under this condition, small changes in gravity correspond to relatively large displacements of the beam. The gravity change is compensated for, and thus measured, by forcing the beam back to the horizontal position. In early L & R instruments, the horizontal position of the beam was restored by lifting the top end of the zero-length spring through a sophisticated mechanical system (LaCoste and Romberg 2004). Since the beginning of the 2000s, it has been replaced by a capacitive position indicator, to monitor the position of the beam, and an electrostatic feedback system, to keep the beam in a fixed null position. When an electronic feedback system is used, the accuracy of the recordings with L & R devices (1 Hz sampling rate) can be better than $1 \mu\text{Gal}$ for averages over time-windows of 1 min. L & R instruments remained the standard for geophysical gravimetry until a new generation of relative spring gravimeters was developed by Scintrex Ltd., in the late 80s. Scintrex gravimeters are microprocessor-based, automated instruments, featuring a vertically hanging quartz spring and a capacitive displacement transducer/electrostatic feedback system able to detect movements of the proof mass and to force it back to a fixed null position. The displacement transducer can determine changes in the length of the spring as small as 0.2 nm, thus removing the need for astatization, which largely eliminates errors arising from mechanical imperfections in the zeroing system. Spring-based gravimeters are affected by instrumental drift, a gradual change of the zero position due to changes in the elastic properties of the spring, that occur slowly over time. For L & R gravimeters, the drift is on the order of 1 mGal per month, but decreases as the meter ages down to $<0.5 \text{ mGal}$ per month. The quartz spring based Scintrex instruments have a tendency towards stronger long-term drift. Budetta and Carbone (1997) found that, under the severe field conditions encountered on active volcanoes, Scintrex devices provide a better measurement precision than L & R instruments. They also showed

that the strong drift of Scintrex gravimeters ($\sim 1 \text{ mGal/day}$) can be reduced to acceptable standards (within about $20 \mu\text{Gal/day}$) by use of the real-time automatic compensation feature. Scintrex remained the major competitor of L & R for about ten years. In 2001 the two companies merged to form LaCoste & Romberg—Scintrex, Inc. (LRS), which later became the parent company of Micro-g. Nowadays, LRS and Micro-g capture most of the market available for land spring-based relative gravimeters with two products: the Micro-g/LaCoste gPhone (Fig. 1) and the Scintrex CG-6 gravimeters (Fig. 2), the successor to the CG-3M and CG-5 models. The Scintrex CG-6 and its predecessor, the CG-5 (Fig. 2), are well suited for measurements at active volcanoes, thanks to their compact shape, limited size/weight, insensitivity to



Fig. 1 Relative gravimeters that can be used for continuous measurements at a fixed site: the iGrav superconducting gravimeter, produced by GWR, the gPhone spring gravimeter (formerly called Portable Earth Tide Gravity Meter), produced by Micro-g/LaCoste and the L & R D spring gravimeter, no more in production



Fig. 2 Relative gravimeters especially designed for time-lapse measurements along a network of observation points. The Scintrex CG-5 (left) and CG-6 (right) gravimeters

shocks, and automated features. They have thus been the standard for time-lapse observations at volcanoes since the mid-to-late 2000s (e.g., Bagnardi et al. 2014; Calahorrano-Di Patre et al. 2019). Conversely, the gPhone (Fig. 1), which is primarily intended for recording gravity time series (continuous observations), is not especially suited for use in harsh field conditions. To improve its performances (precision = $1 \mu\text{Gal}$; system noise = $3 \mu\text{Gal}/\sqrt{\text{Hz}}$), some features were introduced, like a double-oven system, allowing for a higher degree of temperature stabilization, and the lack of indicators of tilt and beam position—a condition probably reflecting the

need to minimize the number of vents in the chassis of the instrument and better insulate the sensor against ambient temperature and pressure changes. As a consequence, the gPhone is nearly 3 times larger and >4 times heavier (13 vs. 3.2 kg) than previous L & R models (e.g., the D and G meters; Fig. 1), requires a continuous power supply of about 100 watts (by comparison, the power supply required by a L & R D or G meter with electronic feedback system is about 10 W) and needs continuous communication with its control system, including a laptop computer, during setup operations (unclamping and leveling the meter, centering the proof

mass in the feedback range). These features are not compatible with deployments in hostile field environments where devices are run on solar panels and batteries and need to be as easy as possible to transport and deploy. This explains why most studies of continuous gravity at active volcanoes have been accomplished using either old L & R meters, no more in production (e.g., Jousset et al. 2000a; Carbone et al. 2012, 2015; Poland and Carbone 2016, 2018), or the main competitor to LRS/Micro-g spring gravimeters, namely, the Burris gravity meter (BGM) (e.g., Gottsmann et al. 2011; Carbone and Poland 2012). The latter is manufactured by ZLS Corporation (Austin/Texas, USA) and is also based on the zero-length spring concept of L & R.

Superconducting Gravimeters

The proof mass of a relative gravimeter can be suspended by systems other than a physical spring. Superconducting gravimeters (SGs) employ the magnetic levitation of a superconducting Niobium sphere in a field of superconducting persistent coils (Goodkind 1999; Hinderer et al. 2015). The first SG design was introduced by Prothero and Goodkind (1968). The basic sensor configuration has remained unchanged since that time, even though improvements in many aspects of the original design have transformed the SG from a prototype experiment into a reliable research tool (Hinderer et al. 2007), now produced and commercialized by GWR Instruments (Fig. 1). By utilizing the perfect stability of supercurrents, a completely reliable, nonmechanical spring is created (Goodkind 1999). Hence, SGs are unaffected by ambient parameters and feature sub- μGal precision (0.05 μGal over 1-min averaging) and negligible instrumental drift (<0.5 $\mu\text{Gal}/\text{month}$). Nevertheless, since the superconducting state is reached at temperatures of <9.2 K, SGs are operated inside a dewar filled with liquid helium. The equipment of a SG thus includes a cryogenic refrigerator and a helium tank, implying that the host facility must have enough installation surface (≥ 2 m^2) and must be supplied with main electricity (the cryogenic

refrigerator system requires ~ 1.4 kW of continuous power). Despite installation sites with these characteristics are hardly found in the summit zones of tall volcanoes (close to the active craters, where the strongest changes often develop), the high precision and long-term stability of SGs could make their use of interest, even if they are deployed relatively far from the active structures (Carbone et al. 2019). The above observations, coupled to the high cost of SGs, dictate that the choice to install (or not) an SG at an active volcano must be subordinated to a careful study, aimed at verifying that the installation site is suitably located with respect to the locus of volcanic activity to ensure that signals of interest are likely to be detectable.

MEMS Gravimeters

The suspended-mass design has also been adopted to develop a microelectromechanical system (MEMS) gravimeter. MEMS are microscopic mechanical devices, made from semiconductor materials. They have the advantage of being mass-producible, light-weight and low-priced. MEMS-based accelerometers first appeared in the 70s and became much more ubiquitous with the introduction of car airbags, in the 90s, and smartphones, in the 2000s, where they are employed, respectively, to detect sharp decelerations, indicative of a car crash, and to monitor the orientation of the device, thus adjusting the screen accordingly (Middlemiss et al. 2018). MEMS accelerometers have been developed that achieve extremely good sensitivity (Pike et al. 2016); however, they do not feature a long-term stability allowing them to track slowly varying gravitational signals. Middlemiss et al. (2016) demonstrated a MEMS device with a sensitivity of 40 $\mu\text{Gal}/\text{Hz}$, down to 10^{-6} Hz. This sensor was used to measure the Earth tides over a period of 19 days (Prasad et al. 2022). The MEMS sensor introduced by Middlemiss et al. (2016; Fig. 3) thus marked the transition from accelerometer to gravimeter. In this device, the mass and the supporting springs are etched monolithically from a single piece of silicon and the four symmetric springs exploit a geometric anti-spring design. This design enables

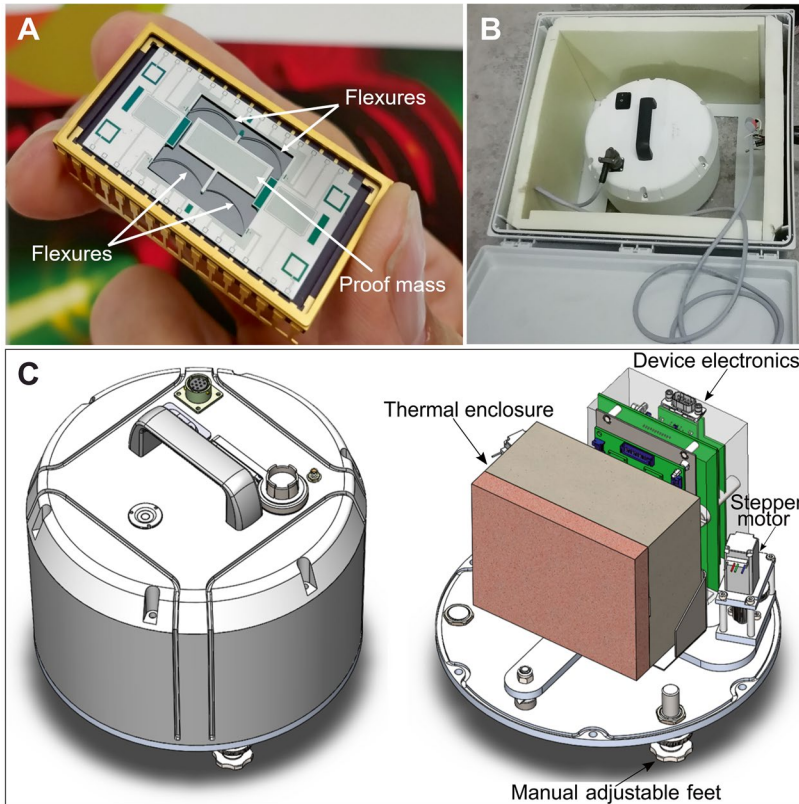


Fig. 3 The MEMS gravimeter developed by the University of Glasgow (Middlemiss et al. 2016). **A** Silicon layer with the MEMS gravimeter, in its ceramic-lead package. **B** Prototype of the device ready for continuous data acquisition. **C** 3-D rendering showing how the

different components of the device are mounted inside the 2-part external moulded shell (top with communication ports and circular aluminum base). Modified after Carbone et al. (2020)

a decreased spring stiffness, implying that the proof-mass will move more for a given change in gravity. A softer spring, however, comes at the cost of decreasing the robustness of the sensor; a working resonant frequency must thus be sought allowing the best compromise between robustness and sensitivity (Prasad et al. 2022). In earlier prototypes (Middlemiss et al. 2016), an optical shadow sensor was used to measure the displacement of the proof mass. This system was later replaced by a capacitive read-out circuit, exploiting two sets of metal comb electrodes (Carbone et al. 2020). Temperature fluctuations alter the Young's Modulus of the silicon flexures, which in turn alters the spring constant of the MEMS device, causing apparent gravity changes which may be much stronger

than the real ones. According to Prasad et al. (2018), temperature of the MEMS gravimeter has to be controlled to the order of 0.2 mK, to allow a sensitivity of 10 μGal . To achieve this, the MEMS sensor developed at the University of Glasgow is housed in a nested enclosure including (i) a lead-ceramic hybrid package within which the sensor is sealed (Fig. 3) and (ii) two thermal enclosures surrounded with polyisocyanurate, each fitted with a Proportional-Integral-Differential closed loop heater control system, utilizing temperature sensors and heaters (Carbone et al. 2020). Despite they were shown to track tidal gravity changes (Middlemiss et al. 2016; Prasad et al. 2022), MEMS gravimeters have not been demonstrated to detect the gravity changes induced by volcanic processes (a few

to a few tens of μGal , over time scales of minutes to months). Nevertheless, these devices represent a promising new opportunity to advance volcano gravimetry in the near future, through the deployment of extended arrays of continuously recording gravimeters (Carbone et al. 2020).

2.1.2 Absolute Gravimeters

The design of classical absolute gravimeters is based on the free fall method. The development of these instruments was possible only when electronics, quartz clocks, and vacuum technology made it possible to reach the required accuracy. The first transportable free-fall absolute gravimeter (FFAG) was developed starting in 1968 at the Istituto di Metrologia “G. Colonnetti” (now Istituto Nazionale di Ricerca Metrologica, Torino; Cerutti et al. 1974). Nowadays, the most widely used FFAG is the FG5 (Niebauer et al. 1995; Fig. 4), developed at the Joint Institute for Laboratory Astrophysics (JILA) and commercialized by Micro-g/LaCoste. It exploits the free fall of a corner-cube reflector at vacuum pressure. The free-fall trajectory of the corner cube is monitored very accurately using a laser interferometer

and referenced to the “super spring” (Hinderer et al. 2002), a system which provides isolation against anthropogenic and natural microseismic noises for the reference mirror of the interferometer, thus improving the precision of the instrument by two orders of magnitude (Van Camp et al. 2017). The FG5 features an accuracy of 2 μGal , while the system noise is 15 $\mu\text{Gal}/\sqrt{\text{Hz}}$ at a quiet site. This device is large and heavy (~ 300 kg; required floor space of ~ 3 m²), has a limited operating temperature range (10–30 °C) and requires a facility supplied with main electricity to house the instrumentation. The FG5 is thus not well-suited for use under field conditions. Nevertheless, some authors successfully used this device to monitor and study active volcanoes (Kazama and Okubo 2009; Greco et al. 2012; Kazama et al. 2015).

Besides the FG5, Micro-g/LaCoste also produces the A-10 (Fig. 4), a FFAG optimized for fast data acquisition in harsh field conditions (Ferguson et al. 2008). With respect to the FG5, the A-10 is lighter (~ 100 kg), more compact, less power-hungry (average power consumption of ~ 200 W), and can operate under a broader temperature range (-18 to $+38$ °C). That comes at the cost of reduced accuracy and precision



Fig. 4 FFAGs produced by Micro-g/LaCoste. Left: the FG5 on operation in the summit of Mt. Etna, inside a temporary protecting facility. Right: the A-10 used to perform discrete measurements at La Soufrière de Guadeloupe

(accuracy = 10 μGal ; precision = 10 μGal after 10 min at a quiet site).

Instruments based on matter-wave interferometry with cold atoms provide an alternative to classical FFAGs. The performance of absolute cold-atom gravimeters were demonstrated in the laboratory (Freier et al. 2016; Wang et al. 2018) and outside laboratories, using transportable prototypes (Ménoret et al. 2018; Bidet et al. 2020). Instead of a macroscopic test mass, these instruments exploit a cloud of laser-cooled atoms, whose free-fall acceleration is measured by means of laser interferometry. They take advantage of the wave-matter duality of atoms, which are used as both test mass and wave to measure the traveled path. This technique offers several advantages, both in terms of absolute performance (the atoms are fundamental objects whose properties are well understood) and instrument operation: with no moving mechanical parts under vacuum, atomic instruments are the only absolute gravimeters suited to perform continuous measurements for extended intervals (several months to years). The LNE-SYRTE

cold atom gravimeter, developed by a research group based at the Observatoire de Paris, supplied the know-how for the first commercially available cold atom gravimeter—the Absolute Quantum Gravimeter (AQG; Fig. 5), now marketed by Exail (formerly Muquans; Ménoret et al. 2018). The AQG achieves a sensitivity of $\sim 50 \mu\text{Gal}/\sqrt{\text{Hz}}$ (1 μGal after ~ 45 min of integration) in quiet places, a long-term stability of 1 μGal , a station-to-station repeatability of 2 μGal and an accuracy better than 15 μGal (Carbone et al. 2020). To enhance its performance against ambient microseismic noise, which affects the stability of the retro-reflecting mirror, the AQG is fitted with an active compensation system. The latter is based on an accelerometer attached to the top of the sensor head, which precisely measures the ground vibrations transmitted to the mirror. Their impact on the atomic interferometer is calculated and compensated for in real time (Ménoret et al. 2018). In the case of the AQG installed at Mt. Etna, the active compensation system was enhanced by replacing the classical accelerometer with a broadband

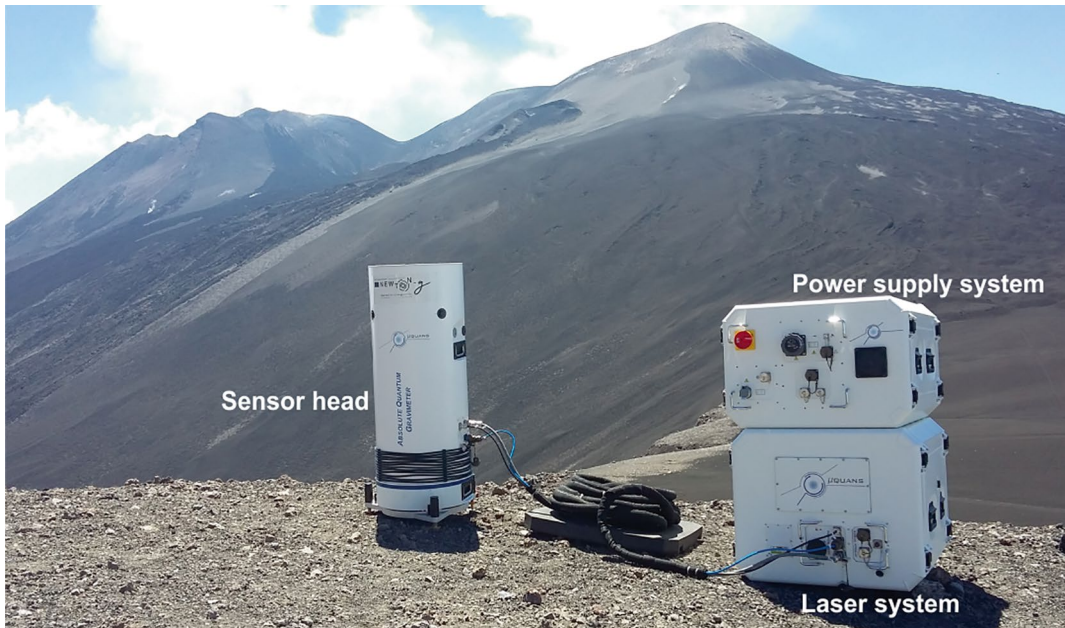


Fig. 5 The AQG-B, produced by iXblue (formerly Muquans), pictured against the summit craters of Mt. Etna, before the instrument was installed in the facilities

of the Pizzi Deneri volcanological observatory (2800 m elevation; Antoni-Micollier et al. 2022)

seismometer (Antoni-Micollier et al. 2022). This allowed to achieve suitable performance, even during phases of high volcanic tremor.

2.2 Gravity Measurements at Active Volcanoes

Gravity changes over time are detected either through repeated measurements, usually accomplished with a single instrument (although sometimes with 2 or 3 devices), which is moved through a network of fixed benchmarks, or through continuous measurements, where the gravimeter acquires a long time series, while installed at a given site. As for repeated measurements, the interval between two successive campaigns should be adequate to fit the expected time-scale of the driving processes, in order to avoid aliasing. Nevertheless, external factors (accessibility of the survey area, eruptive activity, weather conditions, availability of personnel and funding), rather than scientific considerations, often constrain the time span between successive surveys. In the majority of cases, repeated gravity measurements are accomplished through relative spring-based devices, which are easily transportable and do not require much time to set up and record a measurement. When using these instruments for repeated gravity measurements, great care must be taken to minimize instrumental effects, which would otherwise overwhelm the relatively small gravity changes caused by volcanic activity. In particular, spring gravimeters are affected by instrumental drift and tares (sudden jumps in meter reading due to mechanical or thermal shocks; Rymer 1989). During a gravity survey, drift coefficients and tare sizes are assessed either by reoccupying the same point at different times during the same day, or by repeated measurements of the gravity difference between adjacent pairs stations (Watermann 1957). When a suitable survey procedure is followed, the error affecting the gravity data collected in the framework of a campaign of measurement can be restricted to $<10 \mu\text{Gal}$ (Rymer 1989; Budetta and Carbone 1997). The long-term instability

of spring gravimeters dictates that, during each survey, a reference station must be measured outside the active area, where it is assumed that time gravity changes are negligible. Relating the gravity data acquired during each measurement campaign to the reference station makes data acquired in the framework of different campaigns comparable with each-other. However, possible small variations at the reference station due to man-made, hydrological, and other effects will increase the overall error budget for time gravity changes detected through repeated measurements. This limitation can be addressed by using portable absolute gravimeters. However, these instruments cannot be afforded by most research institutions and monitoring agencies and are, in general, not straightforward to use in challenging environmental conditions. In areas where there is no guarantee of temporally constant gravity at the reference site (e.g., small volcanic islands with no sites far enough away from the active structures), time-lapse gravity measurements can only be accomplished if an absolute device is available (Furuya et al. 2003).

2.3 Main Non-volcanic (and Non-instrumental) Effects

In order to retrieve the component of the gravity signal driven by volcanic processes, data must be reduced for effects due to non-volcanic sources (see, e.g., Eq. (1) in Forster et al. 2021). Among these effects, the strongest is Earth tide, which is caused by the gravity of the Moon and Sun, and whose peak-to-peak amplitude reaches $>300 \mu\text{Gal}$. Using suitable models, this effect can be corrected down to the $<1 \mu\text{Gal}$ level (Ducarme 2009).

Atmospheric pressure changes affect gravity measurements by (i) the direct Newtonian attraction of the air column above the measurement point and (ii) the deformation of the Earth's surface caused by the load of atmospheric masses (Torge 1981). A local air pressure recording and a single admittance factor (standard value = $-0.365 \mu\text{Gal}/\text{mbar}$) allow correcting for about 90% of pressure-driven gravity effects

(Merriam 1992), whose amplitude is usually within 10 μGal (Carbone et al. 2003a; Jousset et al. 2000a).

Changes in the orientation of Earth's rotation axis (polar motion) induce changes in the centrifugal acceleration and in gravity, occurring almost entirely over a period of approximately 14 months. In mid-latitude regions, the peak-to-peak magnitude of gravity fluctuations induced by polar motion reaches 10–13 μGal (Wahr et al. 1995; Xu et al. 2004). Independent techniques (i.e., very long baseline interferometry) allow precise determination of the polar motion data and, using the time series of pole coordinates, as provided by the International Earth Rotation Service, it is possible to calculate the gravity effect at a given location and remove it from the observed data.

Changes in groundwater mass can induce gravity changes of a few to a few tens of μGal (Güntner et al. 2017; Hemmings et al. 2016), over a wide range of time scales (hours to years; Creutzfeldt et al. 2008). The contribution of groundwater to time-variable gravity is often not easy to determine, as it depends on several overlapping components, including, precipitation (both rainfall and snowfall), evapotranspiration, and water runoff from the storage beneath the installation site (Forster et al. 2021). The lack of one or more input parameters and a poor knowledge of other influencing factors may limit the possibility to accurately constrain the gravity effect of hydrological variations (Hemmings et al. 2016). In most cases, water table data are not available for the entire area surveyed by repeated gravity measurements. Workarounds include space–time interpolation of the available water table data (Battaglia et al. 1999) and extraction of the hydrological component of the gravity signal through filtering techniques (Carbone et al. 2003b). Assessing the hydrological gravity effect may be further complicated by changes in water-mass storage which occur above the water table (i.e., within the unsaturated zone). The latter can induce significant gravity changes (tens of μGal ; Hemmings et al. 2016) over relatively short time scales, which are independent of the water table elevation.

In cases where the survey area is close to a lake, changes in the water level can induce significant gravity changes. This effect can be forward modelled if records of the lake levels are available (e.g., Miller et al. 2017).

3 Interpretation of Volcano-Related Gravity Changes: Models

Gravity changes measured at active volcanoes are usually analyzed in conjunction with the corresponding ground deformation. Coupled with analytical and numerical modelling approaches, the joint study of deformation and gravity changes allows to set constraints on the spatio-temporal volume and mass changes which occur in the sub-volcanic plumbing system, during phases of magma injection or withdrawal.

Most analytical formulations used to retrieve the characteristics of the causative volcanic sources from the available geodetic data rely on the assumption that the medium embedding the source is a homogenous, isotropic, elastic, semi-infinite space with flat upper surface (Mogi 1958; Hagiwara 1977; Okubo 1992). This is a strong assumption, which hardly corresponds to the setting of most volcanoes. Indeed, many volcanic areas present a steep topography (Beauducel and Carbone 2015; Currenti et al. 2007), and are characterized by complex crustal heterogeneities (Gudmundsson and Brenner 2004), structural discontinuities, and plastic or viscoelastic rheologies (Trasatti et al. 2003), which contradicts the “half-space” assumption. Despite the above limiting simplifications, analytical solutions are still widely utilized, since they are tractable and easy to implement, thus can be easily employed as forward models for inverse methods (e.g., Jousset et al. 2003; Chauhan et al. 2020).

Variations in the vertical component of gravity, which is the only component typically measured in volcano gravimetry, arise from (i) changes in the overall mass of the magma mixture (liquid, gas and crystals) stored in the source reservoir and (ii) changes in the

distribution of the host-rock mass, caused by the subsurface displacement field. These contributions can be accounted for by three main terms (Bonafede and Mazzanti 1998; Currenti et al. 2007):

$$\Delta\rho(x, y, z) = -\mathbf{u} \cdot \nabla\rho_t + \Delta\rho_i - \rho_t \nabla \cdot \mathbf{u} \quad (1)$$

where, $\mathbf{u}$ represents the displacement field, ρ_t is the embedding medium density and $\Delta\rho_i$ is the density change from the new intrusive mass of magma. The first term in (1) (δg_1) arises from the shifting of density boundaries within the crust. The second term (δg_2) refers to the mass change within the source volume. The third term (δg_3) arises from density variations in the host medium (volumetric strain), reflecting the changes in source volume. The total gravity change observed at the ground surface is thus given by (Fig. 6):

$$\delta g = \delta g_1 + \delta g_2 + \delta g_3 + \gamma \delta h \quad (2)$$

where, γ is the free-air gravity gradient, while δh is the elevation change of the observation point. The standard value of γ is $-308.6 \mu\text{Gal/m}$; however, in volcanic areas with prominent

topography, the real value can differ from the standard one by as much as 80% (Vajda et al. 2020). The last term in (2) is the free-air effect and is caused by the change in the vertical distance between the observation point and the Earth's center.

The analytical formulation most commonly used to interpret gravity changes and ground deformation from active volcanoes is the ‘‘Mogi model’’ (Mogi 1958). It approximates magma injections and withdrawals at depth as changes in pressure and mass within a spherical source buried in an elastic half-space (Mogi 1958; McTigue 1987). When they are caused by the expansion/contraction of the Mogi spherical source, the terms δg_1 , δg_2 and δg_3 in (2) are given by the analytical expressions reported below (Hagiwara 1977):

$$\delta g_1 = 2\pi G\rho_t \delta h \quad (3)$$

$$\delta g_2 = G[(\rho' - \rho_t)\Delta V + \Delta\rho V] \frac{z}{(z^2 + r^2)^{3/2}} \quad (4)$$

$$\delta g_3 = -\frac{2}{3}\pi G\rho_t \delta h \quad (5)$$

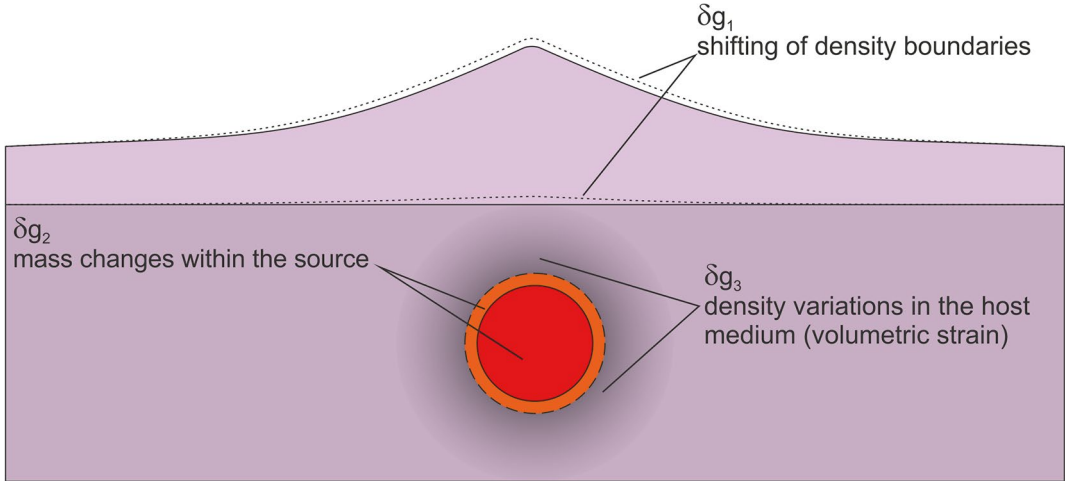


Fig. 6 Schematics of the main contributions to gravity changes measured at volcanoes, due to changes in the subsurface density distribution. δg_1 arises from the displacement of density boundaries (including the free surface); δg_2 reflects the mass changes occurring within the magma in the pressurized source reservoir; δg_3 reflects modulation of the changes in source volume by

host-rock compressibility. δg_2 consists of two different terms: (i) filling of the newly created volume, when the chamber expands, with a material having a different density with respect to the displaced host rock (ii) possible mass change at constant volume within the source (e.g., magma compressibility)

where, G is the universal gravitational constant; ρ' is the average density of the fluid causing the unrest (i.e., the volume expansion/contraction); $\Delta\rho$ is the average density change within the original volume of the chamber; V is the pre-unrest volume of the magma chamber; ΔV is the volume change undergone by the magma chamber; δh is the elevation change at the ground surface; z and r are vertical and horizontal distances between observation point and mass center of the source. δg_2 consists of two different terms, one related to the fact that, when the chamber expands, the newly created volume is filled with a material whose density (ρ') is different from the displaced host rock (ρ_r). The second term accounts for the possible mass change at constant volume within the source, which may results from, e.g., compressibility of the magma already present in the chamber. Considering that:

$$\delta h = \frac{3}{4\pi} \Delta V \frac{z}{(z^2 + r^2)^{3/2}} \quad (6)$$

if the volume change occurs without any change in mass ($\rho' = 0$; $\Delta\rho = 0$), δg_2 becomes:

$$\delta g_2 = -G\rho_r \Delta V \frac{z}{(z^2 + r^2)^{3/2}} = -\frac{4}{3} \pi G\rho_r \delta h \quad (7)$$

In this particular case, the overall gravity change resulting from country-rock deformations vanishes ($\delta g_1 + \delta g_2 + \delta g_3 = 0$, see Eqs. (3), (5) and (7); Walsh and Rice 1979) and the gravity change observed at the ground surface will only reflect the free-air effect. Conversely, if $\Delta\rho = 0$ and $\rho' \neq 0$, combining the above equations gives (Eggers 1987):

$$\delta g = \left(\frac{4}{3} \pi G\rho' + \gamma \right) \delta h \quad (8)$$

Relying on the fact that gravity and elevation changes are related linearly through the Mogi's solution and that $\delta g/\delta h$ is independent from the position of the observation point (Eq. 8), some authors proposed to use the ratio to assess the likelihood and type of volcanic processes at work (Rymer and Williams-Jones 2000;

Gottsmann et al. 2003). In particular, when volcanic activity is regulated by the dynamics of a pressurized magma chamber whose characteristics can be adequately approximated by the Mogi's model, from the study of the $\delta g/\delta h$ gradient it is possible to derive information on the density of the intruding material (e.g., magmatic or hydrothermal fluids; ρ' in Eq. 8) and on possible mass excess or mass deficiency with respect to the expected $\delta g/\delta h$ gradient. Strong deviations may be indicative of "side processes" acting in conjunction with the ongoing magma intrusion/withdrawal and inducing mass changes other than those predicted by Eq. 8.

When the source of the observed gravity changes and deformation cannot be adequately approximated by a spherical shape, analytical formulations other than the Mogi model should be used to interpret the available data. Indeed, the simplification that holds true for a spherical point source, i.e., that the only deformation effect on gravity is the free-air effect (Eq. 8), is not true for other source shapes (Walsh and Rice 1979; Segall 2010) and may lead to bias in the interpretation of the results (Battaglia and Hill 2009). Through combining the analytical formulations derived by Okubo (1992) and Okada (1992), it is possible to calculate the gravity changes and corresponding ground deformation due to a dike-like intrusion (activation of a rectangular tensile dislocation; Chauhan et al. 2020). The "fissure eruption" model, derived by Okubo and Watanabe (1989), allows to calculate gravity changes and ground deformation (vertical component only) induced by the opening of cracks in a narrow fracture zone, under tensile stress (Jousset et al. 2003). These cracks may channel the flow of magma to the surface, thus triggering an eruption (Carbone et al. 2009a, 2014). The sets of equations proposed by Clark et al. (1986) and Yang et al. (1988) allow calculation of the effect of a pipelike (prolate spheroid) source, that can be used to approximate a volcanic conduit. The equations derived by Fialko et al. (2001) and Battaglia et al. (2008) can be used to evaluate the effect of a horizontal penny-shaped body (sill-like intrusion; Battaglia et al. 2006).

Starting from the compound dislocation model (CDM) proposed by Nikkhoo et al. (2017), Nikkhoo and Rivalta (2022) developed point-source analytical solutions for the gravity changes caused by triaxial sources of expansion. The point CDM is composed of three mutually orthogonal point tensile dislocations, constrained to either expand or contract together. The analytical formulation of Nikkhoo and Rivalta (2022) provides a framework for the joint analysis/inversion of deformation and gravity changes, allowing to constrain the parameters of the mass/pressure source without an a-priori assumption on the source shape and, in the case of an elongated shape, orientation.

The half-space and simple-geometry assumptions make analytical models easy to utilize, but can result in misleading volcanological interpretations (Fernández and Rundle 1994; Trasatti and Bonafede 2008). Accounting for (i) possible mechanical discontinuities and heterogeneities of the medium, (ii) the real topography, (iii) complex source geometries, and (iv) non-uniform density distributions throughout the source requires the employment of numerical modeling schemes. Several authors demonstrated that neglecting those factors may result in misleading inferences on the characteristics of the pressure and mass source. Charco et al. (2007) used a 3-D indirect boundary element method and showed that accounting for topography alters both the pattern and magnitude of surface deformation and gravity changes induced by a magmatic intrusion. Trasatti and Bonafede (2008) and Currenti (2014) performed numerical computations based on the finite element method and showed that, accounting for non-spherical sources shapes and medium complexities, such as layering and plastic rheologies, may significantly change the inferences arising from gravity and deformation data. In particular, Trasatti and Bonafede (2008) showed that, when applied to the study of caldera unrest, consideration of the above complexities may lead to inferences on the density of the fluid causing the unrest significantly different than if simple analytical formulations are used. Males and Gottsmann (2021) applied finite element analysis to

systematically explore the influence of subsurface mechanical heterogeneities and topography on surface deformation and gravity changes from magmatic recharge of Erciyes Dağ volcano (Turkey). They showed that predicted vertical displacements and residual gravity changes may vary by factors of up to 5 and >10, respectively, whether or not topography or mechanical heterogeneity are neglected.

However, the advantages of using numerical schemes over simpler analytical approaches come at substantial computational costs, implying that, while numerical model allow the execution of direct calculations, they are, in general, not well suited to data inversions, especially when near real-time monitoring is the target. Furthermore, in order to account for the effect that medium and/or source complexities may have on the budget of gravity changes and deformation, precise knowledge of these complexities is required (for example, exact position and shape of a boundary separating parts of the medium with different characteristics). Otherwise, accounting for such complexities could lead to errors larger than if they were neglected. It is also important to note that gravity data from active volcanoes are often limited and noisy and, since models based on numerical techniques require numerous model parameters, there is a risk of over-interpreting the results (Battaglia et al. 2008). Hence, to derive information on the parameters of the mass and pressure source, the choice of the forward model must be carefully evaluated, taking into account the available information.

When the observed gravity changes are dominated by shallow mass redistributions, not accompanied by subsurface displacement (negligible bulk pressure changes), numerical solutions can be used to forward-model the gravity effect of mass sources whose complex geometry is known from independent information. For example, a numerical model of the summit eruptive vent of Kīlauea was derived, initially based on visual observations and ground-based lidar data (Carbone et al. 2013; Bagnardi et al. 2014; Poland and Carbone 2016) and, later, on structure-from-motion processing of overlapping

aerial images collected using a handheld thermal camera (Fig. 7; Poland et al. 2021). This model was used to precisely calculate the gravity effect of changes in lava level within the vent, with the aim of (i) investigating the density of the lava within the eruptive vent from a continuous gravity time series (Carbone et al. 2013; Poland and Carbone 2016; Poland et al. 2021) and (ii) correcting the results of time-variable gravity surveys, to better detect changes associated with shallow magma storage (Bagnardi et al. 2014).

4 Case Studies

Even though gravimetry has not been applied as extensively as other geophysical methods to monitor and study active volcanoes, numerous papers focused on volcano gravimetry have been produced since the middle of last century and, in most cases, the authors uncovered features of the ongoing volcanic processes that would have remained otherwise “hidden”.

With the aim of showing the potential of volcano gravimetry, in the following, some case studies are presented, focused on results from either repeated, or continuous gravity measurements (see Sect. 2.2).

4.1 Results from Repeated Gravity Measurement

Soon after the development of the first portable gravimeters (Sect. 2.1.1), these devices were utilized to perform time-lapse (or campaign) measurements at active volcanoes. The surveys are usually repeated every few months to years, implying that only long-term volcanic processes can be investigated through campaign gravity measurements.

Early gravity surveys were carried out at Izu-Oshima (Japan; Iida et al. 1952), Izalco (El Salvador; Rose and Stoiber 1969), Pacaya (Guatemala; Eggers et al. 1976; Eggers and Chavez 1979) and Mt. Baker (Washington, USA; Malone 1979) volcanoes. However, in none of those cases the observed gravity changes

could be interpreted unambiguously, due to the lack of ground deformation data, which prevented to distinguish the component of the observed changes due to mass variations within the magma reservoir from the deformation-induced component (Sect. 3). Since the 1980s, thanks to the development of new geodetic instrumentation, most gravity changes observed at active volcanoes have been jointly analyzed and interpreted with the corresponding ground deformation data (e.g., Dzurisin et al. 1980; Eggers 1983; Berrino et al. 1984; Jachens and Roberts 1985; Johnson 1987; Rymer and Brown 1989; Okubo and Watanabe 1989; Battaglia et al. 1999; Jousset et al. 2003; de Zeeuw-van Dalfsen et al. 2006; Bagnardi et al. 2014).

Depending on the characteristics of the processes driving long-term changes (mostly related to the transport, storage and evolution of magma in the crust), different patterns of gravity changes and ground deformation may be produced. Cross-analysis of gravity and ground deformation data allows to obtain information on the source mechanism which cannot be achieved if only one dataset is available. Indeed, while ground deformation can provide insights about volume changes in the underground reservoir, it does not provide constraints on the mass of the intrusion. Conversely, gravity measurements can be used to infer the density of the fluid causing the unrest, thus distinguishing between processes driven by, e.g., magma, gas, or hydrous fluids.

One of the case studies which best demonstrate this comes from Long Valley Caldera (LVC), where a quasi-steady uplift of the central Resurgent Dome occurred in the 1980s and 1990s (Pulvirenti et al. 2021). Gravity measurements at LVC were carried out yearly between 1980 to 1985 and were repeated in 1998 and 1999. The joint inversion of deformation and gravity data pointed to the accumulation of magma, rather than buildup and expansion of hydrothermal fluids, as the cause of uplift (Battaglia et al. 1999, 2003; Fig. 8), thus providing critical information to assess the hazards posed by the caldera unrest. There are other cases where corresponding gravity and

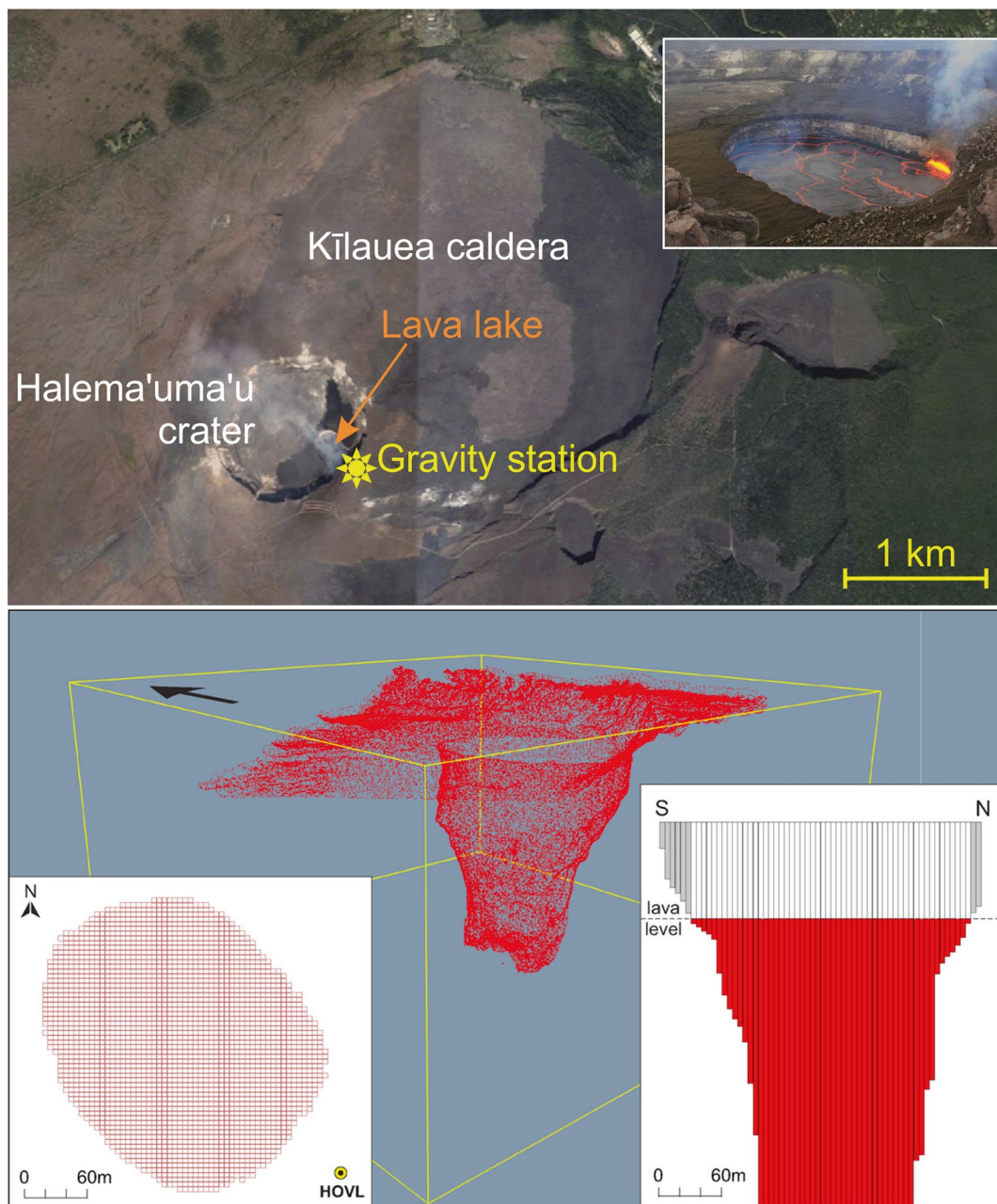


Fig. 7 Top: map showing the position of the lava lake inside the summit Halema'uma'u crater of Kīlauea volcano. The yellow star marks the position of the gravity station and collocated visible/thermal camera. The inset shows a picture of the lava lake as it appeared in April 2018. Bottom: point cloud assembled through Structure from Motion and oblique airborne thermal imagery of the summit eruptive vent of Kīlauea, following withdrawal of the lava lake in May 2018 (the black arrow indicates north direction). Bottom-left insets: plan view,

also indicating the location of the gravity station (yellow circle). Bottom-right inset: north-south cross section of the model used to approximate gravity change due to variations in lava level. The model of the vent interior was created as an array of $5\text{ m} \times 5\text{ m}$ cells (square-based vertical parallelepipeds), whose bottom elevations are obtained from the point-cloud data. At a given time, the volume of lava within the vent is determined by summing the volumes of the lava-filled cells. Modified after Poland et al. (2021)

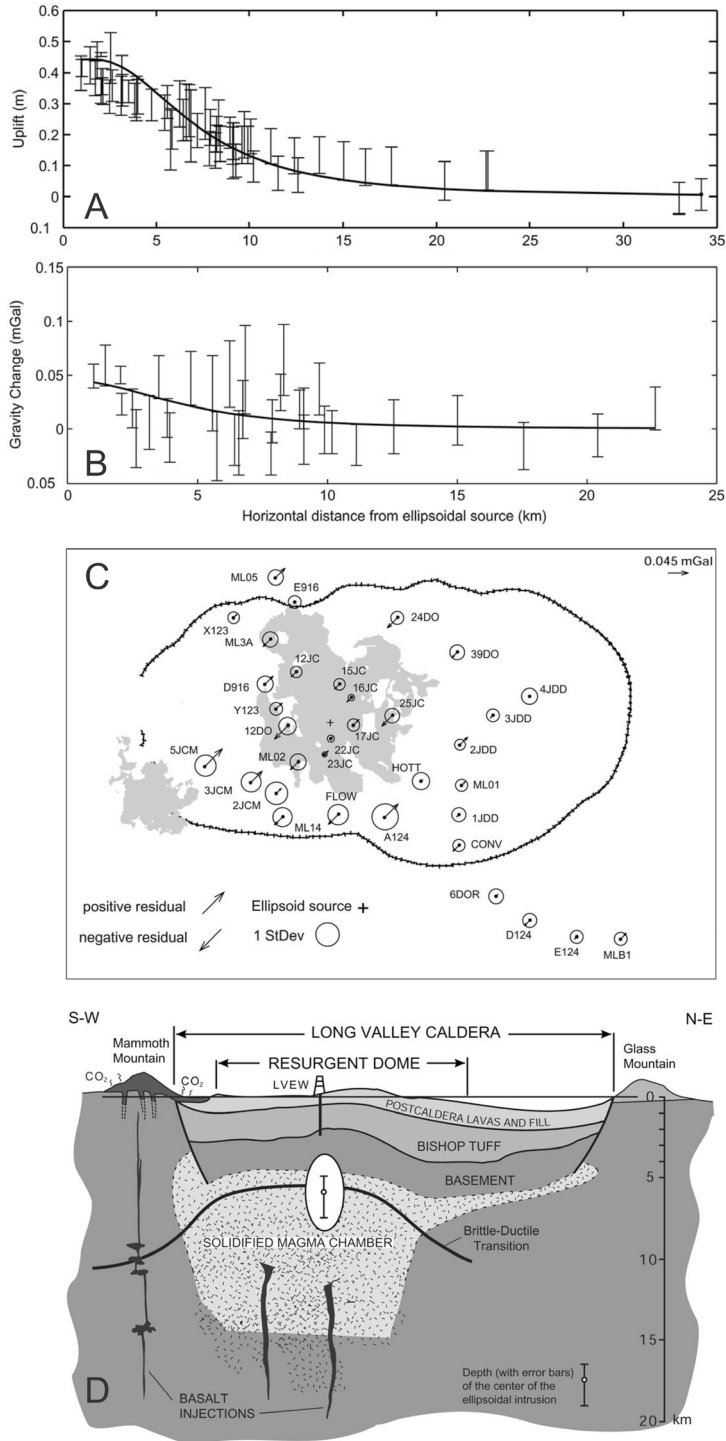


Fig. 8 Gravity changes and deformation at Long Valley caldera, California, from 1982 to 1999. **A** Comparison between observed (error bars) and predicted (solid line) uplift. **B** Comparison between observed (error bars) and predicted (solid line) residual gravity. **C** Areal distribution of the gravity residuals (observed – predicted). Predicted

changes in **A**, **B** and **C** were obtained assuming an ellipsoidal source at 5.9 km depth ($b/a=0.475$; intrusion mass = 0.233×10^{12} kg; volume change = 0.136 km^3 density of the intruded material = 1713 kg/m^3). **D** Cross-section of Long Valley caldera, showing the location of the intrusion. Modified after Battaglia et al. (2003)

deformation data collected at active volcanoes were consistent with the predictions of simplified models, accounting for the effect of magma injection or withdrawal to/from simple-shaped reservoirs. Johnsen et al. (1980) and Torge (1981) observed gravity changes and deformation at Krafla Volcano (Iceland), which could be entirely explained by in- and outflow of magma to and from a reservoir at 3 km depth. Jousset et al. (2003) studied the displacements and gravity variations observed at Usu Volcano (Japan) between 1998 and 2000 and concluded that they were due to the intrusion of new magma prior to the March 2000 eruption.

The joint inversion of gravity and ground deformation data may point to a mass change whose absolute value is less than expected if the driving process involved only accumulation or withdrawal of magma. In this case, either secondary processes occur together with the main ones (e.g., pre-eruptive magma vesiculation accompanying inflation, as proposed by Vigouroux et al. 2008), or a fluid whose density is less than that of magma drives the observed deformation and gravity changes. For example, using gravity and deformation data from Campi Flegrei (Italy), Battaglia et al. (2006) concluded that the 1980–84 inflation episode was due to the injection of a low-density fluid ($\sim 1000 \text{ kg/m}^3$) at shallow depth. The authors interpreted this result as evidence that aqueous fluid and gas migrated towards the caldera hydrothermal system. Similarly, Flóvenz et al. (2022) used gravity data to constrain the density of the fluid that was involved in the uplift episodes before Iceland's 2021 Fagradalsfjall eruption. They obtained a value in the range of $500\text{--}1,200 \text{ kg m}^{-3}$ and concluded that the driving fluid was either CO_2 , or a mixture of CO_2 and magma.

In other cases, the joint analysis of long-term deformation and gravity changes indicated that, even though the pressure and mass sources coincide, the volume change inferred from the deformation is only a fraction of the volume change inferred from residual gravity variations, for any reasonable density of the

fluid injected or withdrawn (Bagnardi et al. 2014). Hence, side mechanisms must activate, allowing mass gain or loss to occur, without the expected deformation. Joint analyses of gravity changes and ground deformation revealed excessive mass gain/loss at different volcanoes, like Piton de la Fournaise (La Réunion; Bonvalot et al. 2008; Fig. 9), Askja and Krafla (Iceland; de Zeeuw-van Dalfsen et al. 2005, 2006) and Kīlauea (Hawaii, Johnson et al. 2010). Bagnardi et al. (2014) analyzed the gravity changes and surface displacements which occurred inside Kīlauea Caldera between 2009 and 2012. They concluded that, while the pressure and mass sources coincided, the volume change inferred from deformation was only 8–9% of the volume changes inferred from residual gravity variations. The authors reviewed different processes able to produce bulk mass change without the expected corresponding volume change. Those include compression/decompression of the magma in the reservoir, substitution of the resident magma with magma having different density, filling/emptying of void space. In particular, magma compressibility can play an important role in producing bulk mass changes associated to limited volume changes. Indeed, while compressibility of degassed basalts at crustal depths is in the range $0.06\text{--}0.1 \text{ GPa}^{-1}$ (Rivalta and Segall 2008), it can reach significantly higher values (up to 3 GPa^{-1}), in the case of volatile-rich magmas stored at depths of $>3 \text{ km}$ (McCormick Kilbride et al. 2016). Residual gravity changes pointing to bulk volumes larger than expected from the associated ground deformation were also observed at Mt. Etna on different occasions (e.g., Budetta et al. 1999; Carbone et al. 2008; Greco et al. 2022) and mechanisms similar to those proposed by Bagnardi et al. (2014) were invoked to explain the mass excess. Currenti (2014) reviewed observations from Mt. Etna during September 1994 to October 1995 (Budetta et al. 1999) and showed that the source geometry may also play a significant role in controlling the relationship between gravity changes and ground deformation occurring at volcanoes (Nikkhoo and Rivalta 2022).

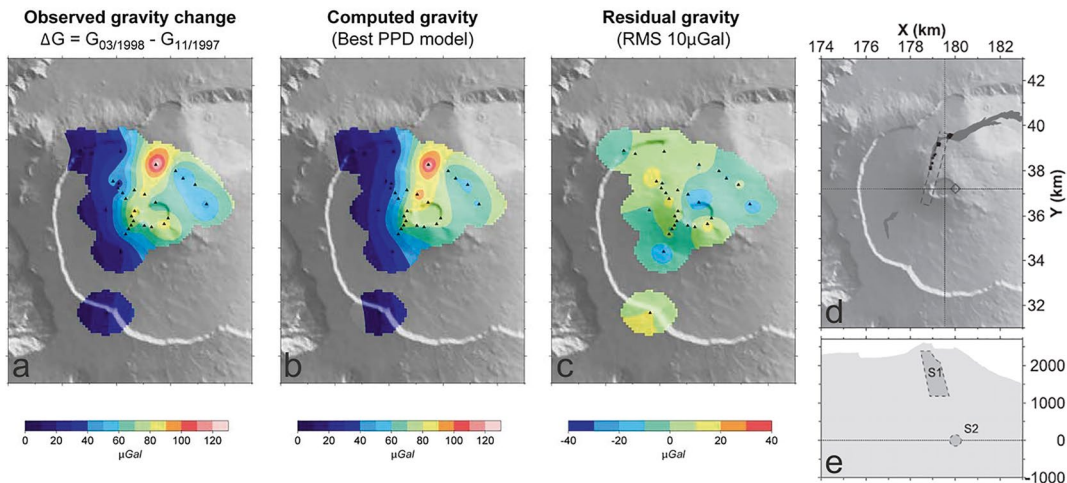


Fig. 9 **a** Gravity changes observed at Piton de la Fournaise, during 4 months before the March 1998 eruption. **b** Computed gravity changes for the best model setup deduced from inversion of the data (panels **d** and

e). **c** Difference between observed and calculated gravity data. **d** and **e** Position of the best-fitting composite source, involving density changes in two volumes at different depth. Modified after Bonvalot et al. (2008)

Whatever the case, it is important to note that, if gravity data are not available, possible excesses of mass gain/loss cannot be detected through the study of deformation data alone, which would lead to misinterpretation of the volcanic processes behind a phase of volcanic unrest.

Especially at volcanoes that host active hydrothermal systems, concurrent gravity changes and ground deformation may be due to mass and pressure sources in different locations. At the Laguna del Maule volcanic field (Chile), Miller et al. (2017) observed an increase in the local gravity field during 2013–2016, reflective of mass addition at 1.5–2 km depth. Although the gravity changes were broadly spatially coincident with ongoing surface deformation, the latter was found to derive from deeper processes, unable to explain the gravity changes. Miller et al. (2017) proposed that the emplacement of a sill at 5 km depth induced an increase in strain and, thus, permeability on shallower structures, promoting influx of hydrothermal fluids, which in turn causes the observed gravity changes. Similarly, Jousset et al. (2000b) found that a common mass and pressure source could not satisfactorily explain the gravity changes and ground deformation observed during the

1996–98 crisis at Komagatake volcano (Japan). Rather, to account for the pattern of observed changes, they proposed a coupled model, involving the emplacement of a magma body at 4–5 km depth and shallow water evaporation, due to the heat rising from the magma body itself.

The study of gravity change is even more important when bulk mass redistribution occurs in the total absence of pressure changes able to trigger measureable ground deformation. Indeed, when that occurs, gravity may be the only parameter allowing to detect the activation of bulk processes possibly leading to an eruption. Once again, Kīlauea provides an excellent example for illustrating the case. Johnson et al. (2010) documented a significant mass increase beneath the volcano's summit caldera, between 1975 and 2008. The study of ground deformation during the same time period indicated that the long-term mass increase occurred in the absence of a significant collocated bulk pressure change. Based on these findings, Johnson et al. (2010) concluded that the 1975–2008 gravity increase was induced by magma accumulation in a preexisting network of interconnected open cracks, which may have formed in response to

the November 1975 earthquake. Another example comes from Masaya volcano (Nicaragua), where the strong 1993–94 gravity decrease occurred without any associated ground deformation. Rymer et al. (1998) interpreted it as due to convection-driven, shallow replacement of relatively dense (degassed) magma by gas-rich material. Long-term gravity changes associated to negligible ground deformation were also documented at Mt. Etna, where the stress field on the volcanic edifice triggers the formation of systems of fractures, allowing for “passive” magma ascent and transport (e.g., Rymer et al. 1993) and also at, e.g., Mayon volcano (Philippines; Vajda et al. 2012), Askja volcano (Iceland; Rymer et al. 2010) and Miyakejima volcano (Japan; Furuya et al. 2003). Finally, it is worth noting that, besides processes involving the transport and accumulation of magmatic fluids, gravity changes with negligible deformation can image the emplacement of volcanic deposits. Between 1993 and 1995, Jousset et al. (2000a) observed strong gravity changes at Merapi volcano (nearly 400 μGal), without any significant concomitant deformation, and interpret it as due to the growth of a lava dome.

4.2 Results from Continuous Gravity Measurement

Repeated campaigns of gravity measurements along extended networks of observation points may offer adequate space coverage of the studied area. Nevertheless, the time resolution is limited by the repetition time of campaign measurements, which is generally on the order of 1 year and almost never shorter than 1 month. Shallow volcanic processes leading to eruptions or changes in eruption style may occur over much shorter time scales (minutes to a few days); to assess their gravity signature, continuous measurements are required. Continuous gravity measurements have been accomplished at active volcanoes since the late 90s, but have remained

relatively rare. Most among these measurements were performed through spring gravimeters (Sect. 2.1.1), which are compact and light, thus easily transportable, and require limited power to perform continuous data acquisition. As such, they can relatively easily be deployed under the harsh conditions encountered in close vicinity to the active structures of tall volcanoes. The main issues that have limited the application of continuous gravimetry to the study of active volcanoes concern the high cost and characteristics of gravimeters. Even the most low-priced gravimeters are about an order of magnitude more expensive than broadband seismometers and continuous GPS stations, implying that, in most cases, it is not feasible to deploy more than two or three continuously running instruments at a single volcano. Hence, the spatial resolution of continuous gravity observations is, in general, not sufficient to assess details on the characteristics of the mass sources. Furthermore, spring gravimeters are affected by instrumental drift, which is usually linear over some days, but becomes nonlinear over longer periods, also because changes in ambient temperature induce instrumental effects that modulate the rate of the drift (El Wahabi et al. 2001; Andò and Carbone 2004). Indeed, the transfer functions between ambient temperature and the signal from continuously recording spring gravimeters were shown to be highly nonlinear, instrument- and setup-specific, and frequency-dependent (Carbone et al. 2003a; Andò and Carbone 2006). Given the difficulties in implementing compensation strategies relying on complex algorithms, the study of time-series from continuously recording spring devices has mostly focused on gravity variations occurring over short time scales (minutes to a few days), which are only negligibly affected by ambient temperature fluctuations, if a suitable setup is adopted for field stations (e.g., Carbone et al. 2003a).

The majority of past studies focused on continuous volcano gravimetry come from Mt. Etna and Kīlauea, where continuously recording

gravity stations were first installed in the late 1990s (Carbone et al. 2003a), and in 2010 (Carbone and Poland 2012), respectively. At Mt. Etna, mechanisms involving local accumulation of gas pockets at shallow levels of the volcano's plumbing system triggered coupled changes in gravity and the amplitude of the volcanic tremor, over periods of 2–12 h (Carbone et al. 2006, 2008; Fig. 10). In particular, the localized mass decrease, resulting from the transient substitution of a denser material (magma) by gas bubbles, triggered the observed gravity changes. Early recognition of such processes

at active volcanoes is of utmost importance, given the implications that local accumulations of volatiles may have for the development of potentially dangerous paroxysms (Allard et al. 2005; Carbone et al. 2015). Continuous gravity monitoring of Mt. Etna also allowed to image the opening of a shallow fracture system and the subsequent “passive” propagation, through the new fractures, of the magma which fed the 2002 NE-Rift eruption (Branca et al. 2003; Fig. 10A). On some occasions, sudden gravity changes occurred simultaneously at two different sites on Mt. Etna, during local low-magnitude

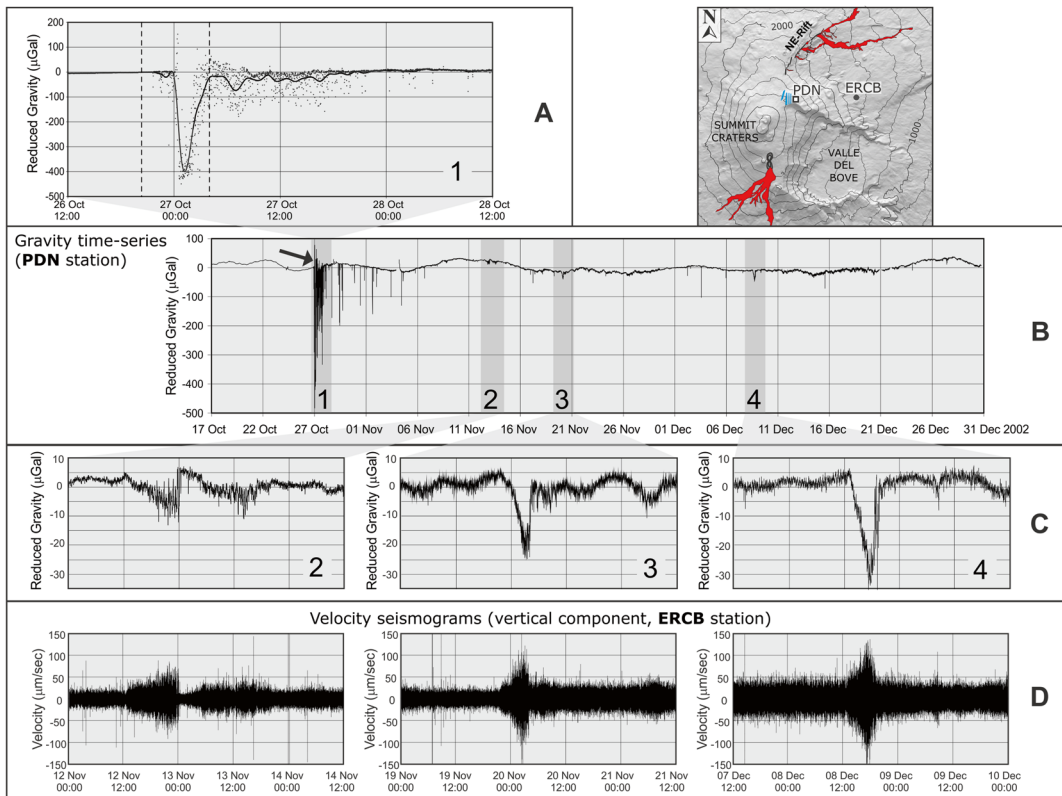


Fig. 10 **A** Gravity time series from PDN station, encompassing the start of the 2002 NE-Rift eruption. The dashed lines mark the start of the seismic swarm before the eruption (left) and the opening of the eruptive fissures (right). **B** Gravity time-series from PDN during 17 October to 31 December 2002. **C** Transient phases of gravity decrease, lasting 6–12 h (marked with darker strips in panel **B**). **D** Transient phases of tremor amplitude increase, occurring simultaneously with the

transient gravity decreases (panel **C**). The sketch map of Mt. Etna, on the top, shows: the position of the PDN and ERCB gravity and seismic station, respectively; the lava flows from the 2002 NE-Rift eruption; the position of the dry fractures that opened before the start of the NE-Rift eruption (in light blue); the position of the vents feeding the effusive and explosive 2002–03 activity on the southern flank; the lava flow they produced. Modified after Carbone et al. (2006)

earthquakes, and were interpreted as a geophysical evidence of the dynamical stress transfer between tectonic and magmatic systems at a local scale (Carbone et al. 2009b).

At Kīlauea, continuous measurements from two spring gravimeters provided the first ever geophysical evidence of fast (time scales of minutes) magma convection in a shallow reservoir (Carbone and Poland 2012; Fig. 11). Continuous gravimetry has also been particularly valuable for gaining understanding about the characteristics of the lava lake within the summit eruptive vent at Kīlauea. In particular, using a 3-D model of the vent geometry (Fig. 7), the cross-analysis of gravity and thermal camera data allowed to retrieve the density of the lava within the upper tens to hundreds of meters of the vent (Carbone et al. 2013; Poland and Carbone 2016). Results pointed to a very low density (within 1000–1500 kg/m^3), thus indicating that Kīlauea's lava lake is extremely gas-rich (>50% porosity). This finding is critical to informing models of lava-lake dynamics and calculations of pressure change in deeper parts of the volcano's plumbing system. In 2018, the continuously recording spring gravimeters captured the onset of the lower ERZ eruption of Kīlauea and the effects of lava withdrawal from the summit and Pu'u 'Ō'ō vents, providing constraints on the timing and style of activity and the physical properties of the lava lakes at both locations (Poland et al. 2021). The gravity change observed at Pu'u 'Ō'ō on 1 May 2018 was by far the largest gravity change ever recorded at any volcano by continuous measurements, both in terms of total magnitude and rate (1500 μGal in 1.5 h; Poland et al. 2021; Fig. 12). Finally, new light was shed on the mechanism behind the so-called gas piston events—minutes-to-hours-long, transient increases in lava level, associated to decreases in seismic energy release, spattering, and degassing—of Kīlauea, through continuous gravimetry (Poland and Carbone 2018). In particular, the accumulation of a shallow magmatic foam, driving the transient change in lava level, was shown to be associated with an increase in the gas content of the magma column, in a general context

of diminished gas emissions from the lava lake during the piston events.

The above-discussed limits of spring gravimeters dictate that, through continuous measurements, only changes over time scales of minutes (e.g., Carbone et al. 2009b; Carbone and Poland 2012), hours (Carbone et al. 2006; Poland et al. 2021) and a few days (Jousset et al. 2000a; Sainz-Maza Aparicio et al. 2014) could be detected. Continuous tracking of gravity changes over longer time scales requires the employment of instruments free from instrumental drift and not (or only negligibly) affected by ambient parameters. SGs (Sect. 2.1.1) feature these characteristics, but their employment for continuous data acquisition at active volcanoes is challenging, since they require a host facility with electricity and a relatively large installation surface. Such facilities only rarely exist in the summit crater area of tall volcanoes, which, coupled to the high cost of SGs (2–3 times higher than the cost of a spring gravimeter), has generally prevented their use for volcano gravimetry. A mini array of three SGs was installed at Mt. Etna between 2014 and 2016 (Carbone et al. 2019) and has worked almost continuously since then. The two instruments at higher elevation are 6.5 and 3.5 km away from the summit active craters of the volcano (Fig. 13). Despite the relatively long distance from the permanently active structures, these SGs have provided valuable and unprecedented information on the processes regulating the activity of Mt. Etna. Indeed, thanks to the high precision and long term stability of SGs (Sect. 2.1.1), volcano-related gravity changes, with amplitudes down to 1–2 μGal , have been tracked over time-scales of minutes to months (Carbone et al. 2019; Fig. 13). Continuous time series from the SGs at Mt. Etna were used to better understand the mechanism behind the December 2018 eruption, thought to also involve formation of void space through increase in the fracturing rate of the medium (Chauhan et al. 2020).

SGs are not the only commercially available devices which can provide precise and almost driftless continuous measurements.

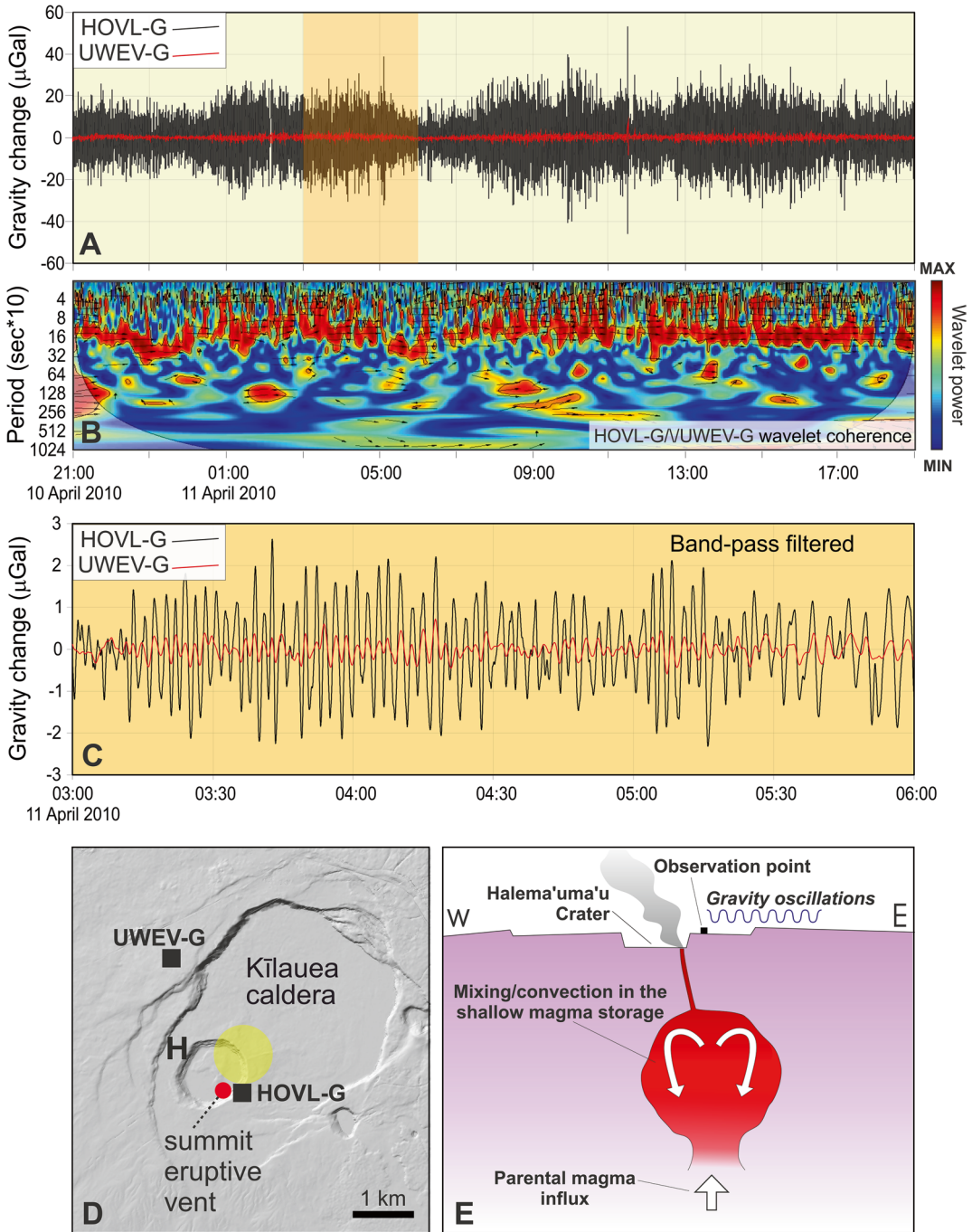


Fig. 11 **A** 22 h of gravity signal from HOVL-G and UWEV-G stations at Kilauea volcano, during 10 and 11 April 2010. **B** Wavelet coherence plot between signals from HOVL-G and UWEV-G. Significant sections are found systematically around a wavelet scale corresponding to ~ 150 s and show in-phase behavior (arrows pointing right). **C** 3-h plot showing band-pass (around ~ 0.0067 Hz) filtered signals from the two gravity stations (shaded area

in **A**). **D** Map showing the position of the two gravity stations, the summit eruptive vent inside the Halema'uma'u (H) crater and the area of magma storage at ~ 0.5 – 1.5 km depth (yellow area). **E** The gravity oscillations with a period of ~ 150 s were interpreted as due to density inversions (convective overturns) in a magma reservoir located ~ 1 km beneath the east margin of Halema'uma'u crater. Modified after Carbone and Poland (2012)

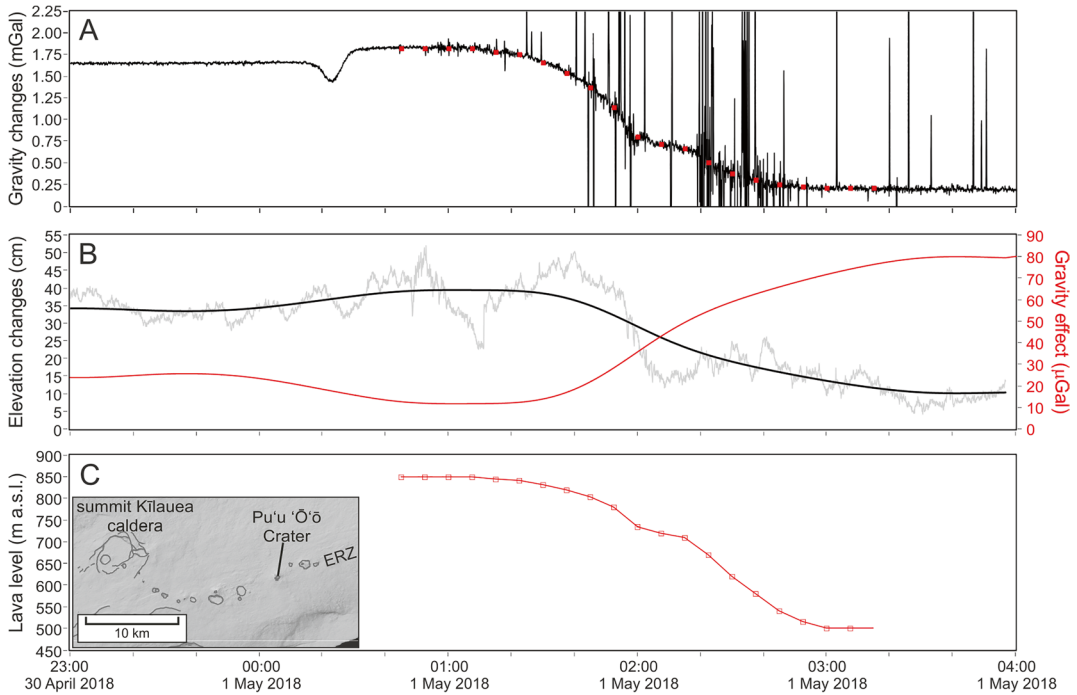


Fig. 12 **A** Gravity changes from Pu'u 'Ō'ō, during 23:00 April 30–04:00 May 1 (UTC). The gravity decrease on 1 May 2018 is by far the largest gravity change ever recorded at any volcano by continuous measurements, both in terms of total magnitude and rate. Red dots are the calculated gravity due to lava level changes shown in (C), assuming a density of the withdrawn material of 1900 kg/m^3 . **B** Elevation change from the GNSS station collocated with the gravimeter. Gray

line is raw high-rate data, and black line is smoothed displacement. Red line is the gravity effect induced by the vertical deformation. **C** Modeled lava level change in Pu'u 'Ō'ō crater, calculated from decimated gravity data. The map in the inset shows the position of the Pu'u 'Ō'ō pit crater, along the East Rift Zone (ERZ) of Kīlauea volcano. The gravimeter was installed only a few tens of meters from the northern edge of the crater. Modified after Poland et al. (2021)

Antoni-Micollier et al. (2022) presented the first time series ever acquired with a quantum gravimeter in the summit area of an active volcano and demonstrated that the field version of the absolute quantum gravimeter produced by Exail (AQG-B; Ménoret et al. 2018; Carbone et al. 2020) can be successfully utilized to continuously monitor and study active volcanoes. The device was installed $\sim 2.5 \text{ km}$ from the active craters of Mt. Etna volcano and provided continuous gravity data with a quality suitable to detect volcano-related gravity changes. Indeed, a comparison involving corresponding 4-month time series from the AQG-B and the SGs at Mt. Etna highlighted correlated gravity variations over time scales of days to weeks, reflective of

bulk volcano-related mass changes (Antoni-Micollier et al. 2022; Fig. 14).

5 Concluding Remarks and Future Directions

The many examples listed in the previous section clearly show that microgravity data may play an essential role in elucidating processes that control volcanic activity. In some cases, gravity is the only parameter which can track bulk volcanic processes, like when magma is injected into pre-existing open space (e.g., Johnson et al. 2010), or when, owing to the compressibility of the resident magma (Rivalta

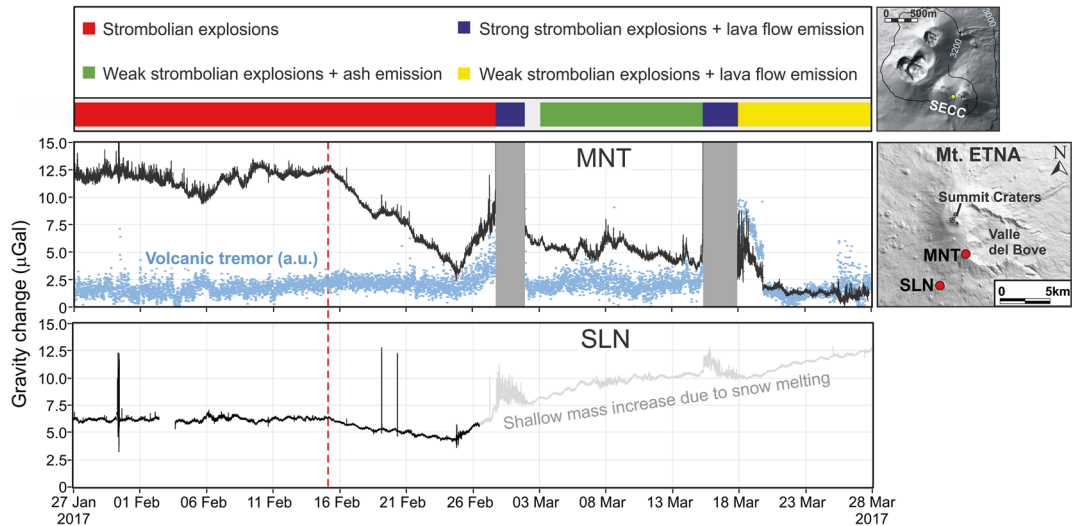


Fig. 13 Top: different phases of volcanic activity from a vent in the South East Crater Complex (SECC) of Mt. Etna, during 27 January to 28 March 2017. Middle: gravity time series from the iGrav SG installed at MNT and map showing the position of the two stations at Mt. Etna equipped with iGrav SGs. The light blue dots are used to show time changes in the amplitude of the volcanic tremor (arbitrary units). Grey strips mark intervals where, due to severe ground shaking, gravity data were

disregarded. Bottom: gravity time series from the iGrav SG installed at SLN. The shadowed part of the time series mostly reflects the groundwater mass increase driven by snow melt. The dashed red line marks the start of the gravity decrease which heralded a phase of sustained strombolian activity. By comparison, no significant variation was observed in the amplitude of the volcanic tremor, during the gravity decrease

and Segall 2008), new mass is added to a reservoir, without significant volume change (Bagnardi et al. 2014). Bulk gas accumulation (Carbone et al. 2015) and changes in the rate of micro-fracturing along fissure zones cutting the volcano edifice (Hautmann et al. 2010; Carbone et al. 2014) are other processes which may induce measurable gravity changes in the absence of other signs. Furthermore, only through the application of microgravity studies to caldera systems one can gain insight into the density (hence, the nature) of the fluid driving a phase of unrest (magma vs. hydrothermal fluids; Battaglia et al. 2003, 2006), which represents a paramount information from the standpoint of risk assessment.

Despite its ability to detect potentially hazardous processes which could otherwise remain “hidden” (see Carbone et al. 2017 and references therein), gravimetry—especially continuous observations—has not been utilized as widely as other geophysical techniques to

monitor and study active volcanoes. Main reasons for that are (i) the relatively high cost of gravimeters (between 100 and 500 kUS\$) and the fact that they are not especially designed for field deployment under difficult conditions; (ii) the ambiguity in the interpretation of time gravity changes, especially under low signal-to-noise ratio.

Cost of instrumentation is not a roadblock issue for discrete gravity measurements, which can be performed using only one gravimeter. High-quality measurement campaigns along extended arrays of points can nowadays be carried out relatively quickly, through automated, compact, light and low-power devices (e.g., the CG-6 Autograv gravimeter by Scintrex; Fig. 2). Conversely, the high cost of gravimeters constraints the number of continuously running devices permanently deployable at a single site. However, old refurbished L & R spring gravimeters (Fig. 1), which come at a much lower price than new instruments, can be successfully used

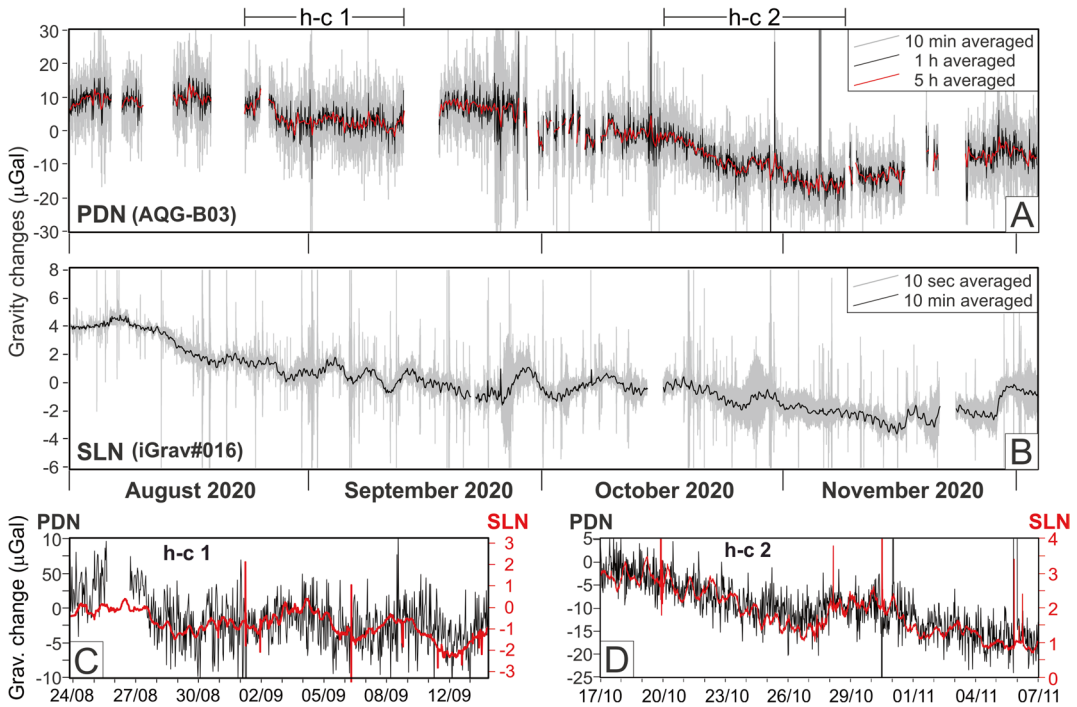


Fig. 14 **A** Continuous time series acquired with AQQ-B03, between August and early December 2020. The instrument was installed at Mt. Etna volcano, in the facilities of the PGN volcanological observatory, at 2800 m elevation, and 2.5 km from the summit active craters. Curves with different colors show the same residual signal averaged over different time scales. **B** Gravity time series observed at SLN station with iGrav#16 SG, during the same period. SLN is at 1730 m elevation and

~6.5 km from the summit craters. h-c 1 (**C**) and h-c 2 (**D**) mark two intervals of higher correlation between the gravity signals from the two stations (late August–mid-September and mid-October–early November). During these intervals volcano-related bulk processes likely activated, capable to induce common gravity changes at the two sites, which are 9 km apart. Modified after Antoni-Micollier et al. (2022)

to continuously track volcano-related changes (e.g., Jousset et al. 2000a; Carbone et al. 2008, 2015; Poland et al. 2021). Data from these devices can be acquired through low-cost and low-power modules (e.g., the Raspberry Pi; Carbone et al. 2020), thus further reducing the overall cost of a continuous gravity station.

Results from Carbone et al. (2019) and Antoni-Micollier et al. (2022) showed that, when it is possible to afford the cost of even one or two driftless (or almost such) gravimeters (e.g., the iGrav SG or the AQQ-B; see Sect. 2.1 and Figs. 1 and 5) and there are the conditions to install them at suitable distance from the active structures of a volcano, important insight into the processes driving volcanic activity can still

be retrieved, despite the poor spatial resolution, especially if gravity data are interpreted in conjunction with independent geophysical information (e.g., Chauhan et al. 2020).

A promising opportunity for volcano gravimetry comes from the ongoing development of MEMS devices. The MEMS gravimeter is currently progressing along the Technology Readiness Level scale (Héder 2017), from a laboratory demonstration (Middlemiss et al. 2016) to a device relevant for geophysical applications (Carbone et al. 2020). Since they rely on the same fabrication techniques used to produce mobile phone accelerometers, MEMS gravimeters have the potential to be much less expensive than commercially available instruments,

implying that new horizons could open for the application of volcano gravimetry. In particular, the availability of a low-cost, low-power, small and light device would permit, for the first time, the deployment of dense arrays of continuously recording gravimeters, thus allowing to follow the temporal changes due to geophysical processes with unparalleled spatio-temporal resolution.

Non-uniqueness is an overriding concern in gravity interpretations, although one should keep in mind that a certain degree of ambiguity is inherent to the interpretation of all geophysical data (Kearey et al. 2002), including those acquired by the most exploited methods for monitoring and studying active volcanoes. The availability of appropriate constraints, namely, auxiliary information on the source of anomaly, can limit these ambiguities. Indeed, in most studies focused on time-variable volcano gravimetry, gravity data were cross-analyzed with and, thus, interpreted in light of independent geophysical and volcanological information (e.g., Battaglia et al. 2003, 2006; Bagnardi et al. 2014; Carbone et al. 2006, 2008). The difficulty in interpreting gravity data from active volcanoes also depends on how non-volcanic effects decrease signal-to-noise ratio. Nevertheless, several studies have demonstrated that, while instrumental effects can be mitigated by adequate surveying techniques, in the case of campaign measurements (e.g., Battaglia et al. 2008), or proper station setups and post-processing corrections, in the case of continuous measurements (Andò and Carbone 2006), local hydrological effects (Forster et al. 2021) can be precisely determined and removed from the gravity signal through models computing changes in groundwater mass from rainfall/snowfall records and soil parameters (Güntner et al. 2017; Hemmings et al. 2016; Kazama et al. 2015).

The above observations are meant to show that none of the factors that have limited the full development of volcano gravimetry is

actually insurmountable. Ongoing and future developments will likely broaden the application of time-variable gravimetry, thus allowing to exploit its full potential to study and monitor, even in near real-time, active volcanoes.

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Monitoring Volcanoes Deformation Based on Synthetic Aperture Radar (SAR) Data

V. Pinel and F. Albino

Abstract

This chapter focuses on the use of Synthetic Aperture Radar (SAR) imagery to detect and quantify surface displacements on active volcanoes. It provides some basic information on the principle and geometry of SAR imagery before detailing how surface displacement maps can be retrieved from the combination of two time-offset acquisitions, either by using phase difference, thus producing interferograms, or by characterizing amplitude shifts by pixel offset tracking. The temporal evolution of the surface displacements can be obtained from the time series analysis of a large number of SAR images. The topic of interpreting displacement fields in order to derive key information in terms of magma storage at depth and transport to the surface by modelling is then widely covered. In particular, the influence of the geometry, position and orientation of the magma source, as well as the acquisition geometry and wavelength of the radar, on the fringe pattern of the interferograms is illustrated on the basis of synthetic cases. The chapter concludes with

an overview of the current state of near-real-time volcano monitoring using SAR imagery in observatories and the main challenges that remain.

1 Introduction

Remote sensing has been identified as an attractive opportunity for volcano monitoring for many years (Sparks et al. 2012; Pyle et al. 2013), which has been confirmed by recent global studies. In particular, Furtney et al. (2018) have shown, based on a systematic study of more than 300 erupting volcanoes over the past decades, that most eruptions are associated with the detection of a signal from space, this signal being either an increase in temperature, an increase in gas emissions or a deformation of the Earth's surface. This is of primary importance considering that less than 20% of active volcanoes can currently be considered well monitored by field instruments (Ferrucci et al. 2012). Among the potential signals recorded from space, it appears that most pre-eruptive signals, occurring prior to eruption, consist of a displacement of the Earth's surface retrieved by Synthetic Aperture Radar (SAR) imagery (Furtney et al. 2018). Although not all eruptive events are preceded by surface displacement detected by interferometry of SAR data

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Table 1 Past and present side-looking orbital SAR missions commonly used in volcanology (as of 2022). Stars point missions characterized by the use of several satellites flying in constellations

Mission	Agency	Period of operation	Band	Wavelength (cm)	Orbit repeat time (days)	Pixel size (m, minimum)
SEASAT	NASA	Jun-Oct 1978	L	23.5	17	25
ERS-1	ESA	Jul 1991 to Mar 2000	C	5.66	3 or 35	30
ERS-2	ESA	Apr 1995 to Sep 2011	C	5.66	3 or 35	30
JERS-1	JAXA	Feb 1992 to Oct 1998	L	23.5	44	18
RADARSAT-1	CSA	Nov 1995 to Mar 2013	C	5.6	24	10
Envisat	ESA	Mar 2002 to Apr 2012	C	5.63	35	20
ALOS	JAXA	Jan 2006 to Apr 2011	L	23.5	46	10
COSMO-SkyMed*	ASI	Jun 2007 to present	X	3.1	16	0.5
TerraSAR-X*	DLR	Jun 2007 to present	X	3.1	11	1
TanDEM-X*	DLR	Jun 2007 to present	X	3.1	11	1
RADARSAT-2	CSA	Dec 2007 to present	C	5.6	24	3
Sentinel-1*	ESA	2014 to present	C	5.6	6-12	3.5
ALOS-2	JAXA	2014 to present	L	23.5	14	10
PAZ	INTA	2018 to present	X	3.1	11	1
ICEYE*	ICEYE	2018 to present	X	3.1	1	0.5
SAOCOM*	CONAE	2018 to present	L	23.5	8	10
CAPELLA*	Capella Space	2019 to present	X	3.1	7	0.5

(InSAR) (Biggs et al. 2014; Ebmeier et al. 2018) and not every deformation signal necessarily leads to an eruption, this type of signal is the most common precursor detected from space of a potential upcoming volcanic eruption. In addition, it has recently been shown that a high magma flow rate detected by InSAR is a reliable signal of impending eruption in basaltic calderas (Galetto et al. 2022). InSAR was first use to retrieve the surface displacement of a volcanic edifice by Massonnet et al. (1995), who demonstrated an apparent deflation of Mount Etna, Italy following an eruption. The benefits of SAR data for volcano monitoring go far beyond the retrieve of surface displacement, as these data can be used to map eruptive deposits or quantify elevation changes affecting volcanic edifices, either due to deposit emplacement, caldera collapse or flank destabilisation (Pinel et al. 2014; Kubanek et al. 2021). In this chapter, we will only focus on the characterization of the surface displacement field on volcanoes from SAR data. This topic has already been described in detail in numerous publications (e.g. Massonnet and Sigmundsson 2000; Pinel et al. 2014, 2022; Poland and Zebker 2022;

Pritchard et al. 2022) but our aim here is to provide the keys to understanding and thoughtfully interpreting the classic products derived from SAR imaging (i.e. interferograms, displacement maps, pixel offsets maps, mean velocity maps).

2 What are SAR Images?

SAR stands for Synthetic Aperture Radar, thus it consists of radar imagery, an active remote sensing method providing an information on the distance between a sensor and a target. Detailed description of SAR imagery can be found in Curlander and McDonough (1992) or Massonnet and Souyris (2008). The sensor onboard of a satellite platform emits an electromagnetic wave, which travels towards the ground surface, hits this surface and is scattered back towards the sensor. The sensor then records the returning wave. SAR imagery operates in the microwave bands, with wavelengths (λ) of the order of the centimeters (see Table 1), characterized by an absence of absorption through the atmosphere. One of the main advantages of radar imagery,

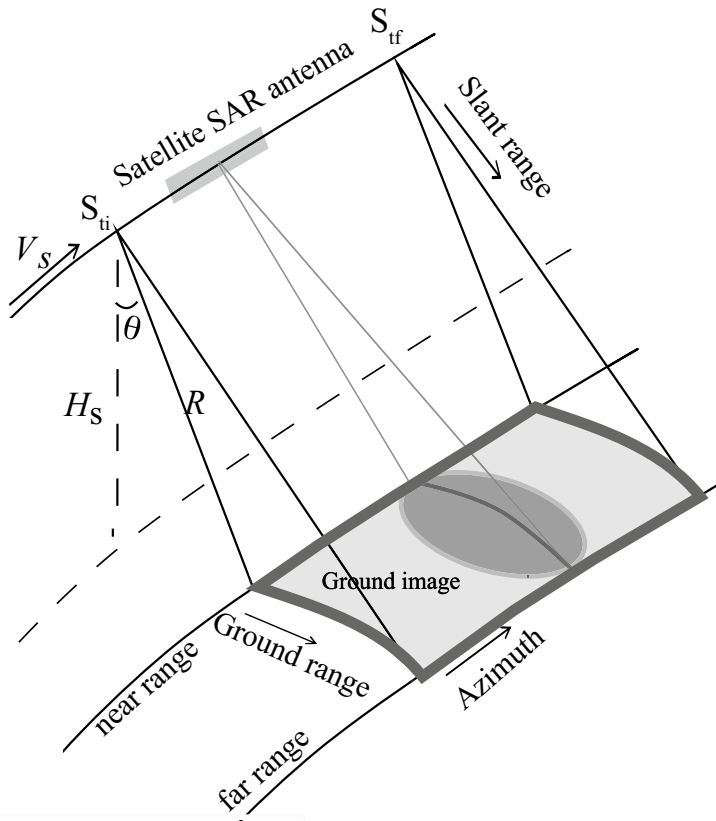


Fig. 1 Acquisition geometry of a radar image. S_{ti} and S_{tf} represent the positions of the satellite's antenna at the beginning (ti) and at the end (tf, typically a few seconds later) of image acquisition, respectively. V_s corresponds to the speed at which the satellite is moving, H_s to the satellite's altitude, θ to the incidence angle and R to the distance

between the satellite and the ground, which increases with the position in "range" in the image (shorter in near range than in far range). The ground image directions are the projection onto the ground of the direction of the line of sight (range) and of the satellite's trajectory (azimuth)

compared to optical imagery for example, is that it does not require daylight and is not limited by the presence of clouds.

The radar information is a complex signal characterized by an amplitude (A) and a phase (ϕ). The amplitude signs the ability of the ground target to send the wave back, so its backscattering properties. The amplitude depends on the local slope, the surface roughness and moisture. The phase depends on the geometric path of the electromagnetic waves and contains an information on the distance. However interactions with the backscattering surface or volume (forest, snow/ice...) can also modify it so that the phase of each pixel is tainted by speckle noise due to the physical properties and spatial distribution of the elementary

targets within the corresponding resolution cell. It follows that the phase of one given image cannot be used directly to retrieve any information on the distance as it appears spatially random. A satellite radar image is characterized by two directions: the "azimuth", parallel to the satellite path and the range (slant range), parallel to the beam or Line of Sight (LOS). While the azimuth direction is horizontal, the range direction has a vertical and a horizontal component, the relative contributions of which depend on the angle of incidence. When referring only to the horizontal component, that is to say the projection of the "slant range" on an horizontal surface, the term "ground range" is used (see Fig. 1).

In case of a radar sensor mounted on a satellite, due to the limited size of the antenna together with the distance from the surface ground (H_s around 800 km), the spatial resolution of raw radar image remains low (around a few km in both azimuth and range directions). That's why the antenna size has to be somehow artificially increased leading to the concept of Synthetic Aperture Radar (SAR). Resolutions in azimuth and range are improved by taking advantage of the Doppler effect and modulating the signal emitted. Based on this and thanks to signal processing, a raw image of relatively poor resolution is transformed into a Single Look Complex (SLC) image with a pixel resolution around a few meters or a few tens of meters. A resolution close to 1 m is reached in Spotlight mode for High Resolution X-band data (e.g. TerraSAR-X, Cosmo-Skymed) and the resolution of Sentinel-1 freely distributed data is around 3 m in range and 15 m in azimuth in the Interferometric Wide (IW) swath mode.

The geometry of SAR images is very different from the one of optical images as two points on the ground can only be separated on the radar image if there are located at different distances from the sensor whereas for optical images, what matters is the difference in viewpoint, or an angular distance. It follows that radar images are not easy to interpret in an intuitive way as we are used to optical imagery through our eye vision. This difficulty is even more pronounced when imaging strong topographic features as volcanic edifices. This concept is theoretically explained in Fig. 2. In particular, you can notice that the resolution in range is decreased on slopes facing the satellite, the worst case being reached when the slope becomes larger than the incidence angle and layover occurs (superposition in the same radar pixel of distinct areas of the ground with upslope becoming closer to the sensor than downslope and the order of pixels in the image becoming reversed). On the contrary, the resolution in range is increased on the side facing away from the satellite, however part of those slopes may be not illuminated by the wave and consequently are not imaged, which corresponds to the shadow effect.

Figure 3 illustrates in a practical way the radar geometry using the example of Mount Fuji,

Japan, a typical stratovolcano, characterized by a conical shape (see the topography in Fig. 3a). The amplitude image of the ascending (flying from South to North) and descending (flying from North to South) Sentinel-1 tracks are displayed in Fig. 3b and c, respectively. Sentinel-1 satellite is right-looking. Due to the geometry of acquisition, raw radar images are mirrored in comparison with the terrain geometry. The ascending image is a flipped image as the first line acquired (top of the image) corresponds to the southern end of the area. The descending image is a flopped image as the first row acquired (e.g. near range, left of the image) corresponds to the eastern end of the area.

On each image the volcano flank facing the satellite (the western flank on the ascending and the eastern one on the descending) has a high amplitude (it appears bright) as it scatters back more energy towards the satellite and it looks narrower than the other flank as the spatial resolution in range of the ground pixel on this flank is lower. Note that the spatial resolution is more affected in the ascending image as, in this case, the incidence angle is lower.

Figure 4 describes how the relative displacement of the ground surface between two passes of the satellite can be retrieved by combining two SLC images characterized by their distance in time (temporal baseline) and in space (perpendicular baseline, because even if the satellite is in the same orbit, its position varies slightly over time). This can be done either by interferometry that is to say by taking the difference between the two phase images ϕ_1 and ϕ_2 as detailed in Sect. 3 or by pixel offset tracking, which means by quantifying pixels displacements between the two amplitude images A_1 and A_2 as detailed in Sect. 4. Each method is largely improved by the use of an additional information on the local topography provided by a Digital Elevation Model (DEM) and the correction of atmospheric artefacts affecting interferograms is often required and can benefit from additional information provided by meteorological model as described in part Sect. 3.4. The precision of the displacement measured during a given time interval is greatly improved by taking advantage of the redundancy of information pro-

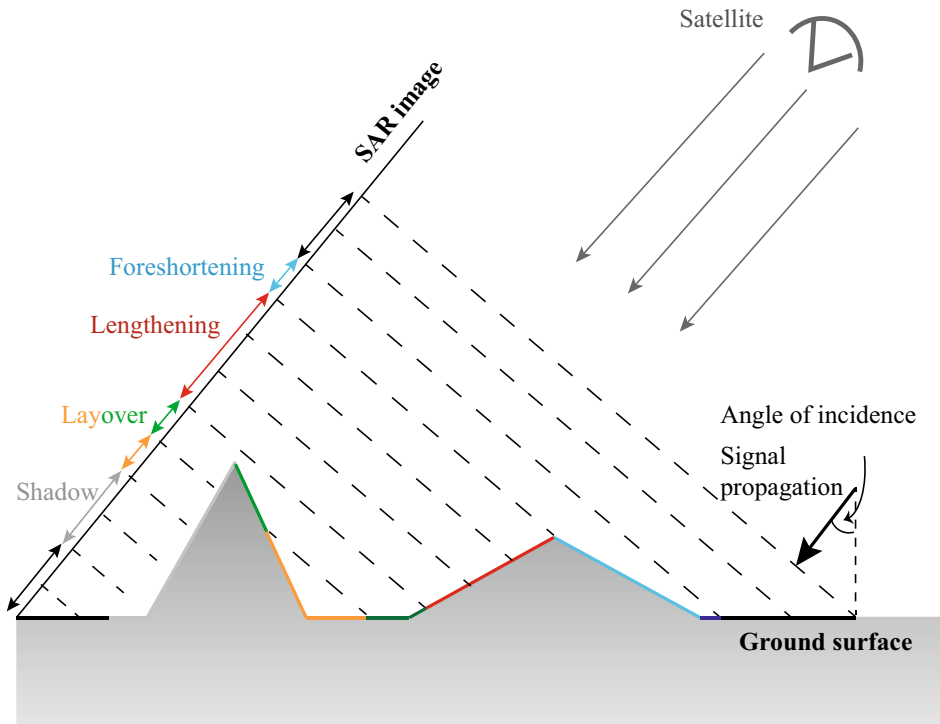


Fig. 2 Imaging geometry. The bottom colored line represents a 2-D slice through a ground surface and the angled black line above represents a single line in a SAR image acquired by a sensor located above, to the right, and flying into the page. The black arrow shows the direction of signal propagation from the SAR sensor and the dashed lines represent perpendicular wave fronts separated by the spatial resolution of the sensor (this spatial resolution being linked to the time delay between pulses of signal emission). The different colors indicate how the ground surface maps to pixels in the range direction of the SAR image. The blue slope facing the sensor is “foreshortened” in the SAR

image, whereas the red slope facing away from the sensor is lengthened, and appears in more pixels despite both slopes having the same length on the ground. The green section of the steeper mountain is “laid over”, appearing in the same pixel as the ground surface well to the right, and the orange lower section of the mountain appears to the left of the upper section in the SAR image, despite being located to the right of it on the ground. The steep gray slope facing away from the sensor is not illuminated by the sensor at all—it is in “shadow”—and does not appear in the SAR image. Modified from Pinel et al. (2014)

vided by the analysis of a time series of several images, as described in Sect. 5.

3 Measuring Surface Displacement by InSAR

3.1 What is an Interferogram?

Repeat-pass interferometry of SAR images (InSAR) consists of calculating the phase difference of two radar images acquired almost at the same location with the same orbit but at different

times, which produces an interferogram (product labelled wrapped interferogram $\Delta\phi_{1-2}$ in Fig. 4). Phase differences results in fringes. The InSAR technique is described in detail for instance by Massonnet and Feigl (1998) and Massonnet and Souyris (2008) or in Dzurisin and Lu (2007) with a focus on volcanoes study. Figure 5 shows an example of a Sentinel-1 interferogram obtained over the Piton de la Fournaise volcano (Reunion island) from images acquired on 8 and 20 October 2021. The signal is clear around the summit area within a major U-shaped structure bounded by a topographic wall and called the Enclos Fouqué

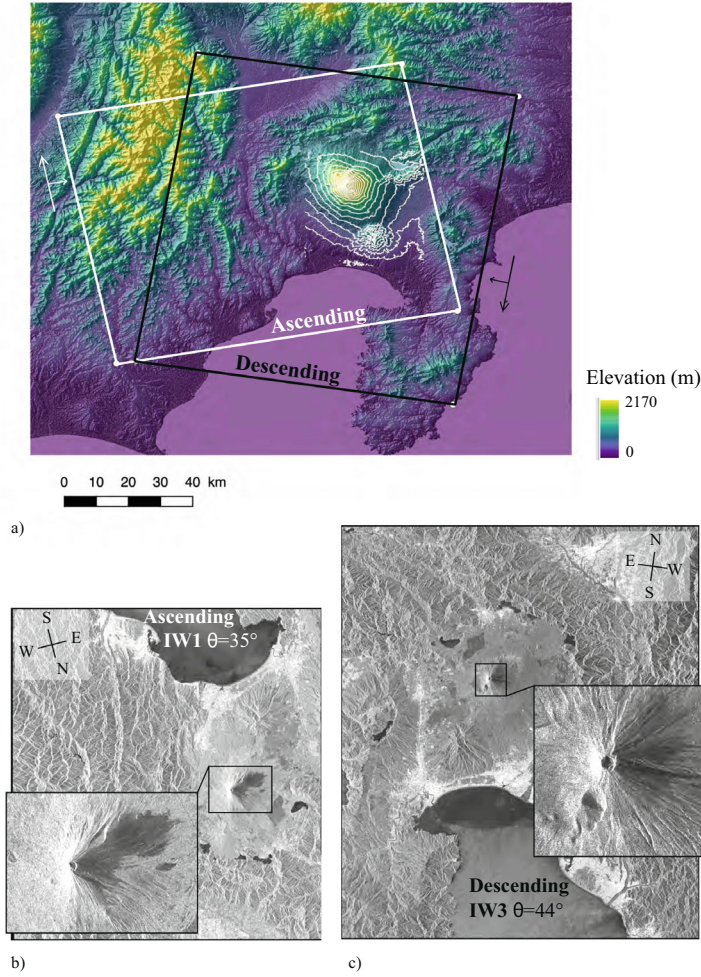


Fig. 3 Illustration of the characteristics of radar geometry using the example of Mount Fuji, Japan, an archetypal strato-volcanoes, characterized by a conical shape and steep slopes in the summit zone. **a** Colour-coded elevation map superimposed on the shaded Digital Elevation Model with 200 m contours in white over the volcanic edifice. Footprints as well as satellite flight and Line of Sight directions of Sentinel acquisitions over Mount Fuji are shown in white and black for the ascending track T039 (subswath IW1 acquired on 18 November 2021) and descending track T046 (subswath IW3 acquired on 11 January 2022) respectively. **b** Amplitude image of the ascending track in radar geometry. Note that the image appears upside down relative to the terrain geometry because the image

is acquired from south to north along the satellite path. The western flank of the volcano is facing the satellite, it scatters back more energy (it appears white) but has a lower spatial resolution (it appears narrower than the eastern flank). **c** Amplitude image of the descending track in radar geometry. Note that the image appears reversed from left to right with respect to the terrain geometry because the image is acquired from near range (eastern part) to far range (western part). The eastern flank of the volcano is facing the satellite, it scatters back more energy (it appears white) but has a lower spatial resolution (it appears narrower than the western flank). The geometric distortion appears less pronounced on the descending track than on the ascending one due to the higher incidence angle

caldera, but the interferogram remains noisy outside on the volcano flanks, which will be explained in Sect 3.2.

Phase difference is the result of different contributions: the topography ($\Delta\phi_{topo}$), the orbital uncertainties, the atmospheric delays ($\Delta\phi_{iono} + \Delta\phi_{trop}$) and the ground displace-

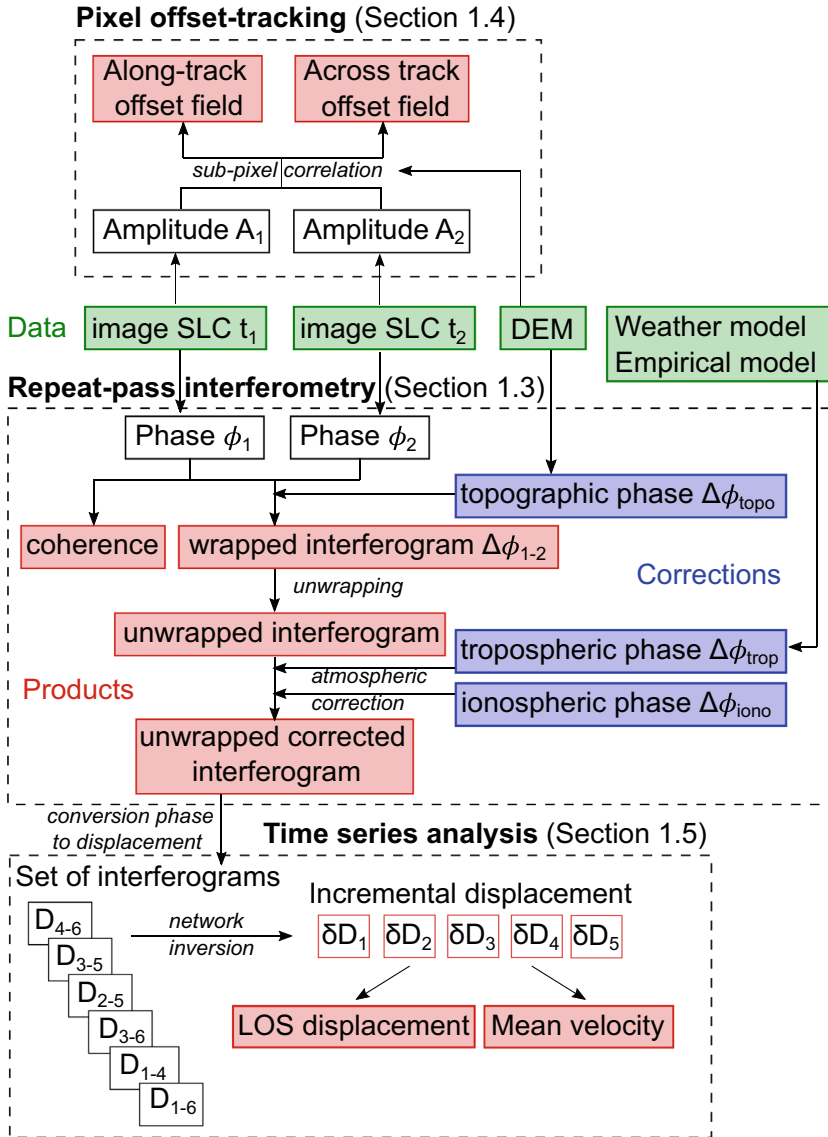


Fig. 4 Flow chart summarising the two ways of obtaining information on the surface displacement field from two SAR images acquired in a similar geometry with a given time interval: pixel offset tracking based on correlation of amplitude images and differential interferometry exploiting phase information. It should be noted that additional information such as DEM and meteorological data is required to insure a correct quantification of the displacement field. Here, corrections for atmospheric contributions are applied to the unwrapped interferogram, but it should

be noted that these corrections can also be applied to the wrapped interferogram, which can improve the unwrapping. LOS displacements can be derived directly by calculating an interferogram between two images, but performing a time series analysis and benefiting from the redundancy of the information greatly improves the precision of the measurement. Similarly, a time series analysis can also be performed on the offset fields obtained by pixel offset tracking

ments. To retrieve the ground displacements, all the others contributions need to be removed or mitigated. Phase difference due to topography ($\Delta\phi_{topo}$) is removed by using an external Digital

Elevation Model (DEM) (see Fig. 4). Phase ramps due to orbital inaccuracies are corrected based on knowledge of the orbits and further reduced using a linear/quadratic approximation.

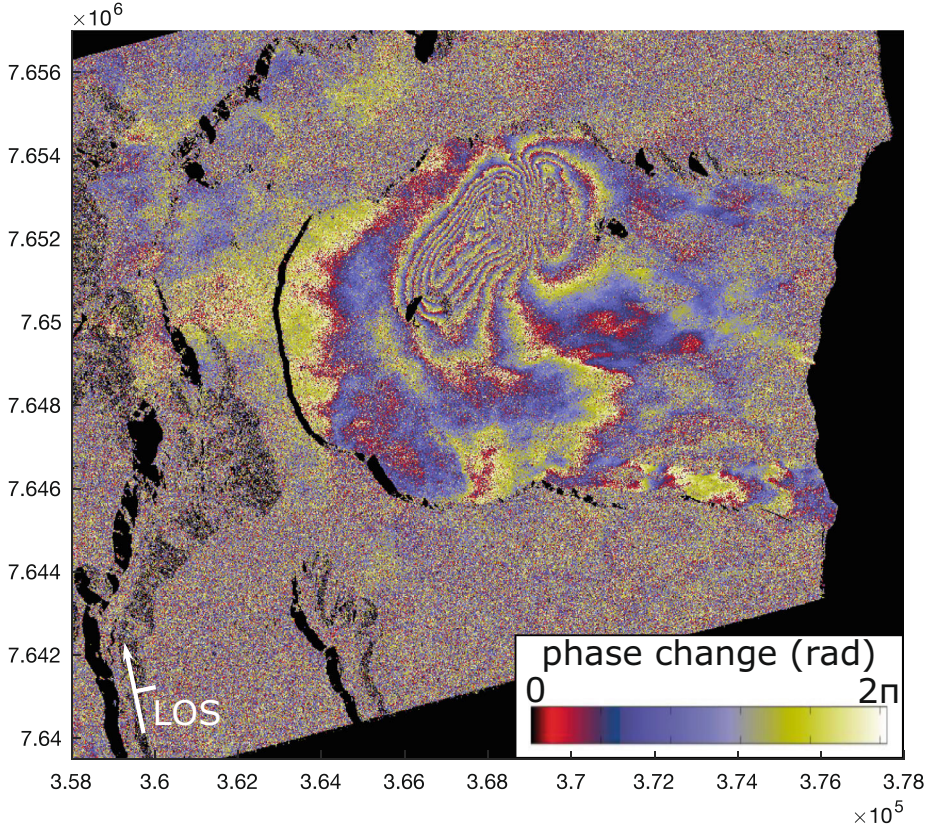


Fig. 5 Sentinel-1 ascending interferogram (Stripmap acquisition mode) spanning the period from 8 to 20 October 2021 at the Piton de la Fournaise volcano on the French island of La Réunion. Coordinates are in UTM (zone 40E)

However, the corrections of the phase difference due to atmospheric delays are much more challenging and will be explained in more details in Sect. 3.4.

3.2 Coherence: a Proxy of the Signal to Noise Ratio

In addition to interferograms, InSAR processing can generate coherence maps (see Fig. 4). The coherence is an estimate of the phase decorrelation of ground targets between two SAR acquisitions, with values ranging between 0 (values close to zero meaning total decorrelation) and 1 (values close to one meaning no decorrelation). This means that the coherence is directly related to the quality of the interferometric signal. In areas with low coherence, the phase difference between

two images will be too noisy to distinguish the fringes (see the volcano flank outside the Enclos Fouqué on the interferogram of Piton de la Fournaise displayed in Fig. 5). Low coherence values are typical for surfaces that are moving rapidly through time such as water bodies, sand dunes or dense vegetation. High coherence values can be found in buildings or bare rocks.

Because phase decorrelation usually increases with time, coherence values for a given area decreases with the increase of the duration of the interferogram. As a result, interferograms with long temporal baseline will be noisier than interferograms having short temporal baseline (see Fig. 6, long temporal baseline interferograms, panels b and d, are noisier than the respective short temporal baseline ones, panels a and c). Phase decorrelation is also dependent on the wavelength of the radar sensor. For short wavelengths, the radio wave

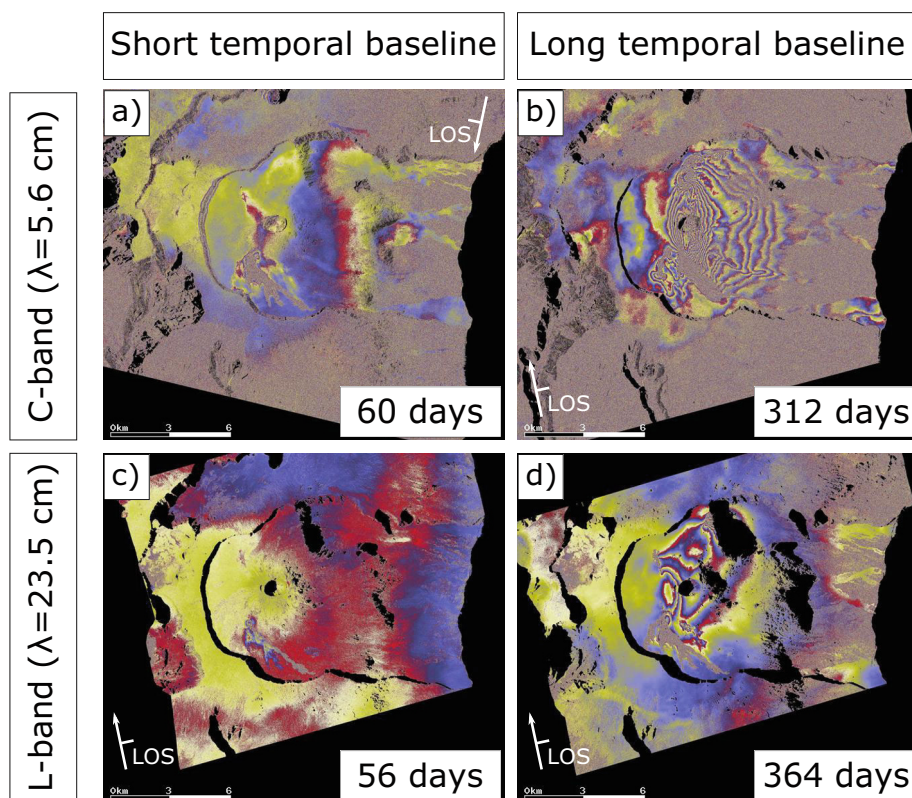


Fig. 6 Four wrapped interferograms calculated at the volcano Piton de la Fournaise (Reunion island). The rows show different types of radar sensor with Sentinel-1 C-band

interferograms (top) and ALOS-2 L-band interferograms (bottom). The columns show the influence of the temporal baseline (e.g. duration of the interferograms)

signal will be scattered by the upper part of the vegetation, and therefore coherence will be low. As an example, C-band interferograms over the Piton de la Fournaise volcano show large decorrelated areas corresponding to vegetated areas, even with short temporal baseline (Fig. 5 or Fig. 6a). On the other hand, L-band radio wave can penetrate the vegetation and therefore the interferometric signal may remain coherent over vegetated areas. As an example, L-band interferograms at Piton de la Fournaise show coherent signal on the vegetated areas (Fig. 6c–d). Note that the L-band interferogram lasting ~ 2 months is coherent over the entire scene whereas the L-band interferogram of ~ 1 year shows some temporal phase decorrelation at the NE corner of the image (Fig. 6c, d).

3.3 From Ambiguous Phase Changes to Continuous Displacement Field

Raw interferograms provide ambiguous phase changes in radian from 0 to 2π . To retrieve the continuous displacement field, it is necessary to unwrap spatially the succession of phase ramps, thus moving from a wrapped interferogram to an unwrapped interferogram as shown in Fig. 4. For each pixel, we need to determine the right multiple of 2π to be added to the value of the phase in order to obtain the exact value of the phase. The fundamental hypothesis for phase unwrapping is to consider that the surface to rebuild is relatively regular and the unwrapped phase is continuous, in other word, no noise is present and the Nyquist criterion is respected during the sampling. These conditions imply that the phase varies within π

between two adjacent pixels. Unwrapping methods used can be divided in two categories : the local methods and the global methods. Whereas the local methods are based on a propagation of the phase value, pixel by pixel along a continuous path, the global methods seek a solution on the whole image that minimises the deviation between the phase gradients measured in the interferogram and those of the result.

Afterwards, the unwrapped LOS change in radian can be converted in meter by using the wavelength of the radar signal λ through the expression:

$$D(meter) = \frac{\Delta\phi(radian)}{2\pi} \frac{\lambda(meter)}{2} \quad (1)$$

Unwrapping is a critical step which may introduces errors in the unwrapped phase retrieved. In particular, the local methods required a use a continuous path between pixels, which is not always possible. When there is an area of low coherence, it introduces a gap in the phase information. The same occurs in case the gradients of displacements are too strong, ending in a phase difference between two adjacent pixel larger than π . The Nyquist criterion is then no longer fulfilled and the phase is lost, this phenomenon corresponds to aliasing. Global methods may also be affected by areas of low coherence or aliasing as, by assumption, they will potentially underestimate the displacement gradients in these areas.

3.4 Mitigation of Ionospheric and Tropospheric Phase Contributions

The main limitation to the use of InSAR for ground displacement measurement is the phase difference induced by the variations of physical properties of the atmosphere between two radar acquisitions, as this phase difference can be wrongly interpreted as ground displacement of several tens of centimetres (Zebker et al. 1997; Hanssen 2001). This is particularly true for studies of volcanoes. Subsequent analysis found that a significant part of the apparent deflation signal

recorded at Mount Etna by the first InSAR study (Massonnet et al. 1995) was due to atmospheric path delay (Delacourt et al. 1998; Beauducel et al. 2000).

Ionospheric effects ($\Delta\phi_{iono}$) can be a source of errors particularly in L-band data, but there are ways to mitigate this effect (Meyer 2011; Gomba et al. 2016, 2017). However, the main atmospheric noise contribution in SAR interferometry comes from the troposphere ($\Delta\phi_{trop}$). Any change in the pressure, humidity or temperature along the path of the radar wave can result in a phase delay, which can be decomposed into a turbulent component and a stratified component. The turbulent component comes from the dynamic of the troposphere, it is generally characterised by short-scale signals (a few kms) in interferograms that are randomly distributed in space and time. This term cannot be modeled but its effect can be reduced by temporal filtering (e.g. Schmidt and Bürgmann 2003). The stratified part is induced by the variations in the pressure, the temperature and the water vapor content profiles across the troposphere between two radar acquisitions. It produces atmospheric fringes in interferograms that are strongly correlated to the topography.

In the absence of complementary information, one efficient way to empirically reduce this effect consists in using the correlation between the phase and the elevation observed on the images in non-deforming areas (e.g. Remy et al. 2003). This method is not perfect as it results in a partial elimination of the displacement signal, particularly on volcanoes, where the ground displacement induced by a magma reservoir centered beneath the edifice is expected to be strongly correlated to the topography. In addition, this method does not correct the turbulent component.

When available, locally acquired meteorological data or delay estimations derived from dense GNSS networks can be used to estimate both the turbulent and stratified component of the tropospheric delay (e.g. Delacourt et al. 1998; Wibley 2002; Li et al. 2006). The strategy, which is the most often deployed, consists in using temperature profiles, pressure and water vapour content provided by global meteorological models in order to calculate the tropospheric delay (Doin

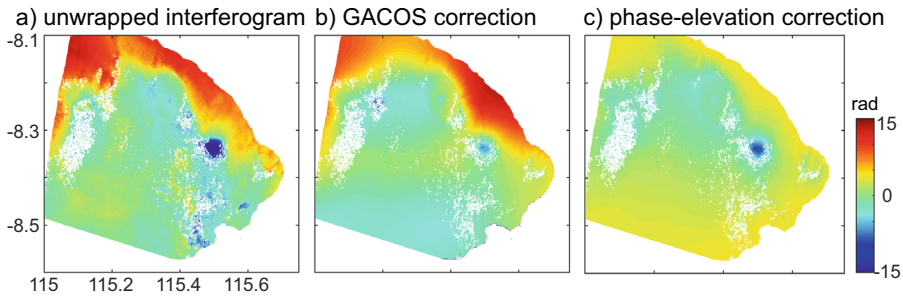


Fig. 7 Comparison of atmospheric corrections calculated at Agung volcano (Bali, Indonesia, modified from Albino et al. 2020); **a** 12-day Sentinel-1 unwrapped interferogram,

b GACOS atmospheric correction based on global weather model; **c** empirical atmospheric correction based on phase-elevation correlation

et al. 2009; Jolivet et al. 2011; Albino et al. 2020). These models, such as GACOS (Generic Atmospheric Correction Online Service as described in Yu et al. 2018) or ERA5 (Hersbach et al. 2020), have a temporal resolution of several hours and a spatial resolution of several tens of kilometres. Because of their spatial resolution, these models are not efficient to correct short-scale turbulent signals (<10 km).

Figure 7a shows a 12-day Sentinel-1 unwrapped interferogram at Agung volcano (Bali, Indonesia), the corresponding atmospheric corrections, using the GACOS weather-based model (Fig. 7b) and the empirical phase-elevation correlation (Fig. 7c). GACOS model is efficient to correct the large wavelength atmospheric signal with amplitude up to 15 radians (~ 6.7 cm) located on the NE coast of Bali whereas it does not correct the small stratified signal of -15 radians located on the volcanic edifice. On the contrary, the phase-elevation correlation enables to better correct the signal on the edifice, but it fails to remove the large signal observed along the coastline.

Note that the small, long spatial wavelength signal observed inside the Enclos Fouqué outside the two lobes of fringes in Fig. 5 may contain some tropospheric signals.

4 Measuring Surface Displacement by Pixel Offset Tracking

The surface displacements field can alternatively be estimated from SAR imagery by calculating pixel offsets between two amplitude images acquired at different time over the same volcanic area (see Fig. 4). Orbit information supplemented by amplitude image correlation is used to put all images in a common geometry by performing a global geometrical transformation. Pixels affected by large displacements between two acquisitions are characterized by residual offsets between the coregistered images. Performing finer amplitude correlation on coregistered images thus provides measurements of surface displacements in both azimuth and slant range directions. The accuracy of the displacement retrieved by pixel offset tracking is typically on the order of one tenth of the spatial resolution of the amplitude image, i.e., a few decimeters to a few meters even if it depends on the coherence (de Zan 2014). The troposphere has a limited effect on the accuracy of pixel offsets. For Sentinel-1 (IW mode), the spatial resolutions of the raw image is about 15 m in the azimuth direction and 3 meters in the slant range direction leading to an accuracy of 1.5 m and 30 cm, respectively, in azimuth (along-track) and range (across-track) direction.

Due to phase ambiguity during the unwrapping step, InSAR method can not measure strong gradients of displacements as phase changes between two adjacent pixels should remain lower than

π (see Sect. 3.3). For long/shallow pressurized magma intrusions, surface displacements in the near field can not be retrieved with differential interferometry, as illustrated by Fig. 8a. Therefore, in these cases, the method of pixel offset tracking provides additional information, by resolving the near-field displacement values in the range direction (Fig. 8b).

Pixel offset tracking method is also very useful in quantifying large summit displacements occurring just before or during an eruption for instance related to dome growth (e.g. Dualeh et al. 2023).

5 Time Series Analysis

Each interferogram measures the displacement field that occurs between two SAR acquisitions. In order to track the temporal evolution of the displacements, it is required to perform a time series analysis, which consists to convert a set of unwrapped interferograms into displacement maps per epoch. A dataset of interferogram is often represented as a network graph in which the edges correspond to the interferograms and the nodes are the SAR images. The x and y -distance between two nodes correspond to the temporal and the perpendicular baseline of the interferogram, respectively. To reduce signal decorrelations, a common approach is to only select interferograms with short spatial and temporal baselines (Small Baseline techniques-SB, Berardino et al. 2002). If some acquisition dates are not connected by the interferogram network, it is necessary to make more or less strong assumptions to reconstruct the phase evolution. Due to the redundancy of the information (e.g. a common date is present in multiple interferograms), it is possible to perform a least-squares inversion of the network to retrieve displacements for each epoch (Schmidt and Bürgmann 2003). Each interferogram $D_{i,j}$ can be related to the sum of the incremental displacements between the two dates t_i and t_j through the matrix G (Fig. 9). The matrix G has the dimension $(m, n - 1)$ with m is the number of interferograms and n is the number of SAR acquisitions. The time series analysis will reduce nuisance signals such as atmo-

spheric effects and residual topography and therefore improve the precision of measurements with the ability for detecting displacement rates of the order of mm/yr. InSAR time series analysis can be divided in two strategies well-described in Ho Tong Minh et al. (2022). Historically, the first approach is Permanent/Persistent Scatterers (PS) InSAR techniques which utilizes individual scatterers dominating the signal from within a resolution cell to track deformation through time (Ferretti et al. 2000). However PS, characterized by a stability of the amplitude are most often associated with stable man made structures and the PS technique is mostly efficient over cities. This technique has been adapted with the aim to catch PS in natural areas, which is more suitable for volcanic edifices study (Hooper et al. 2004). However, the density of PS targets is often low on volcanoes, resulting in a sparse distribution of usable points. It follows that the approach, which is of most interest for monitoring volcanic ground deformation is the one based on Distributed Scatterers (DS). Distributed targets occur in natural environments where many similarly bright scatterers contribute to the information in a resolution cell. It should be noted that in the case of DS, spatial filtering by multi-looking leads to a decrease in the spatial resolution of the derived displacement map compared to the initial resolution of the SAR images. Besides a systematic bias known as fading signal has recently been evidenced in short temporal baseline interferograms (Ansari et al. 2021). Other approaches have been proposed to overcome these problems, for example phase-linking approaches using all possible interferometric pairs based on the full covariance matrix (e.g. Guarnieri and Tebaldini 2008, Mirzaee et al. 2023), the main drawback being their computational cost.

Figure 10b illustrates how a time series analysis shows large-scale inflation reaching a maximum mean displacement rate of about 0.44 cm/yr in Line of Sight located on the flank of Cayambe volcano, Ecuador, whereas single interferograms are too noisy to detect any clear signal (Fig. 10a).

Note that a time series analysis can also be performed on a network of displacement field maps obtained by pixel offset tracking (e.g. Casu et al. 2011).

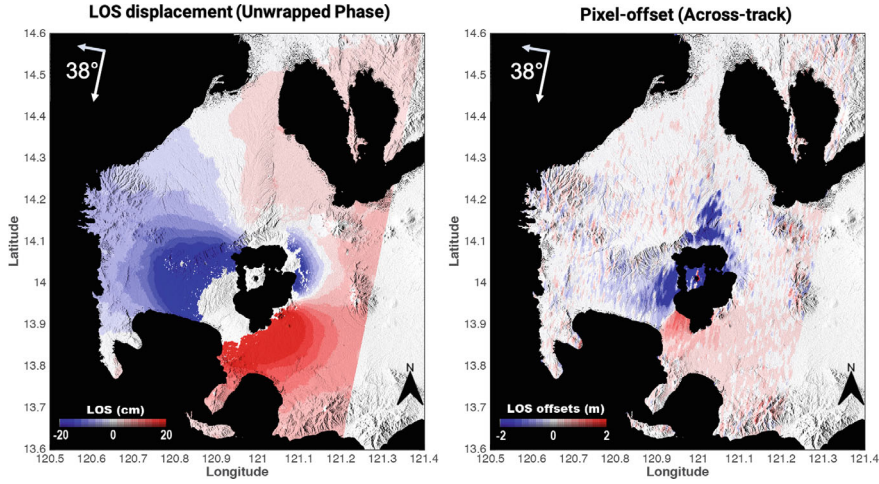


Fig. 8 Displacement field measured at Taal volcano, Philippines using two Sentinel-1 images of the descending track D032 spanning the January 2020 eruption, acquired on January 9 and January 15. **a** LOS displacement field derived by InSAR. Note that the displacement field cannot be retrieved in the near field, on the volcanic island and in

the area to the south-west of the lake, due to the strong displacement gradient affecting these areas. **b** Range-offset displacement maps with a clear signal in the near-field, where no signal could be measured by InSAR (modified from Bato et al. 2021)

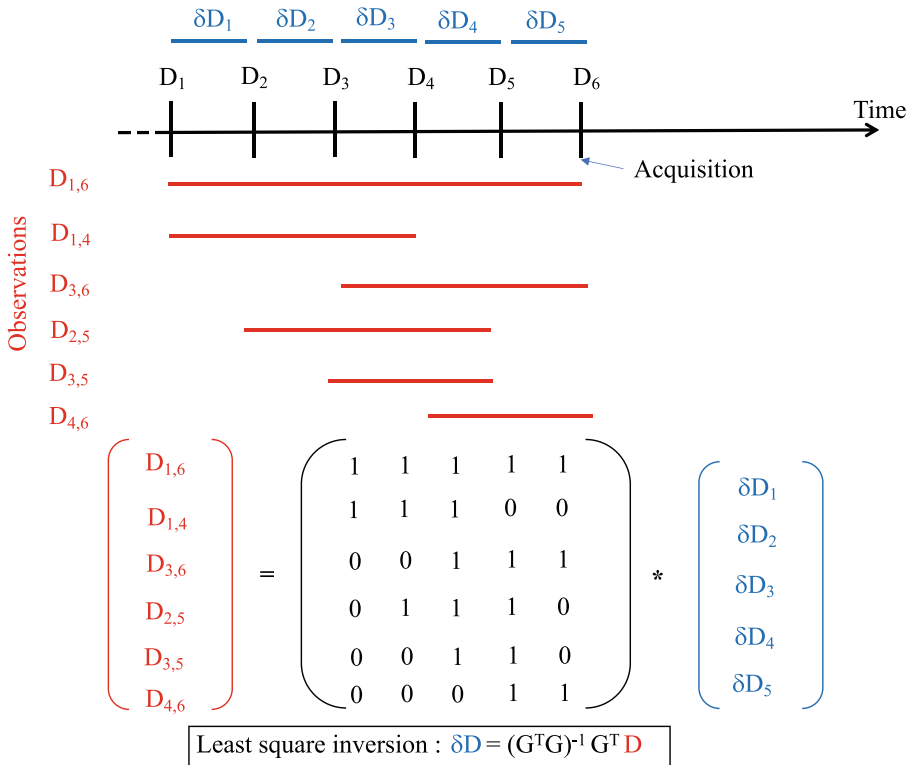


Fig. 9 Principle of the retrieval of incremental surface displacements through the inversion of a network of displacements estimated over various time intervals

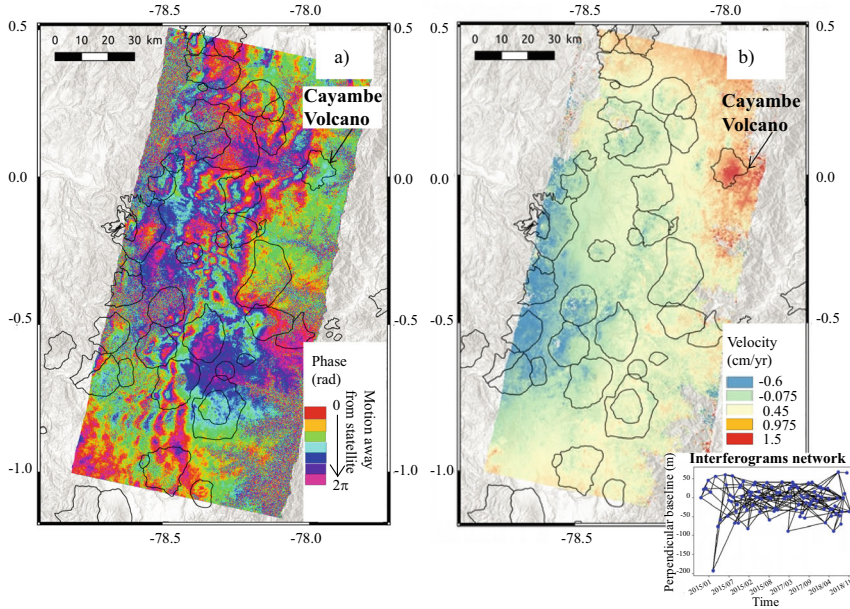


Fig. 10 Highlighting of a small amplitude displacement field by times series analysing of SAR data, example of Cayambe volcano, Ecuador. **a** An unfiltered wrapped interferogram between 24 July 2016 and 17 August 2016 over Cayambe volcano (Sentinel 1 descending track 142). The interferogram contains some tropospheric signal and no obvious signal of ground displacement can be seen. **b** LOS velocity map retrieved by performing a time series analysis (NSBAS as described in Doin et al.

2011) including the 104 Sentinel 1 descending images acquired between October 2004 and November 2018, positive towards satellite. An uplift reaching a maximum mean displacement rate of about 0.44 cm/yr in Line of Sight is observed on the South Eastern flank of Cayambe volcano. The contours of the volcanoes in the area are shown as black lines. The interferogram network is represented. Figures are modified from Espin Bedon et al. (2016)

6 Interpretation of Displacement Fields Derived from SAR Data on Volcanoes by Modeling Magma Emplacement at Depth

Once the surface displacement field is retrieved from SAR images, we can analyse the signals associated with volcanic activity. Statistically, volcanic eruptions are usually preceded by a period of ground uplift that can last from few hours to few decades. Such deformation signals are induced by different physical processes occurring in the magmatic plumbing system. The main causes of surface deformation are (1) the magma storage inside a reservoir located few kilometers depth below the volcanic edifice or (2) the magma propagation from this reservoir towards the surface. Both processes cause an increase in stress in the host rocks, resulting in surface deformation.

Dense and repeated measurements of surface displacements by InSAR are therefore appropri-

ate to provide key information on the dynamics of magma systems (storage and propagation) beneath volcanoes. Here we explain the different types of InSAR signals related to magma storage (Sect.6.1) and transport (Sect.6.2) observed before an eruption because this signal is the most relevant for deducing an imminent eruption. Magma emplacement in the shallow crust can also induce large flank instabilities detected by SAR imagery (e. g. Froger Jean-Luc et al. 2015, Walter et al. 2019) but resulting displacement fields remain more difficult to model (Chaput et al. 2014). Note that additional displacement signals related to eruptive deposits emplacements or even non volcanic processes can be observed on volcanoes, for a complete overview see for instance Pinel et al. (2014), or Pinel et al. (2022).

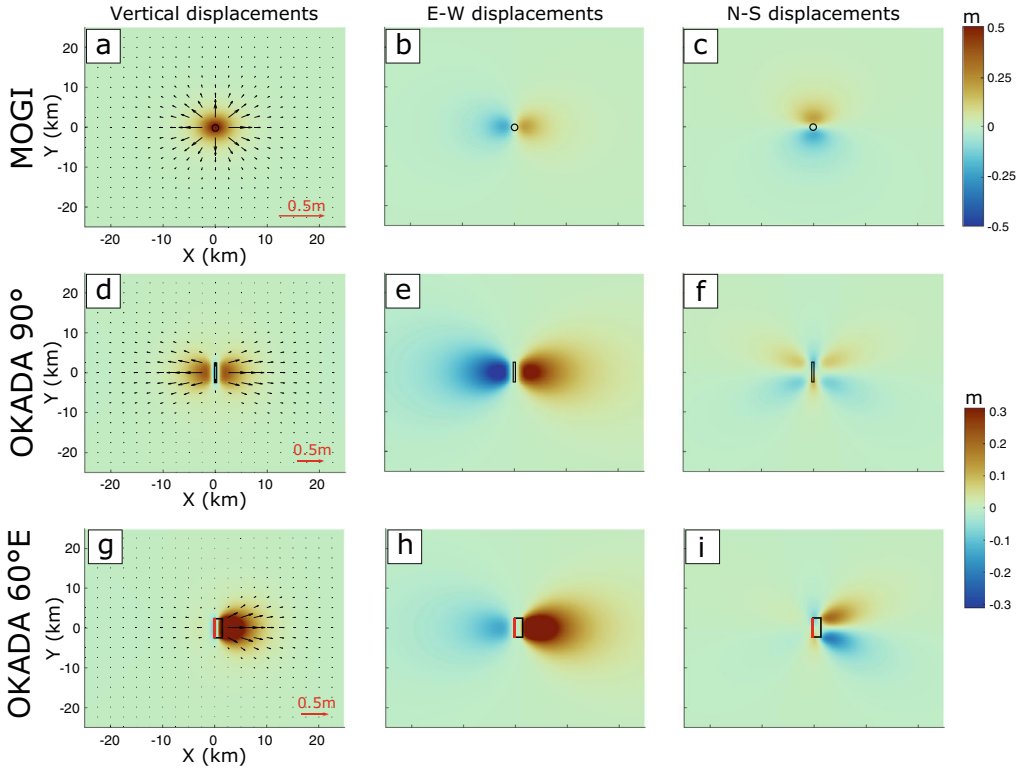


Fig. 11 Displacement field associated with the two most commonly used analytical solutions in volcanology : **a–c** Mogi point source model. A source at 3 km depth with a volume change of $20 \times 10^6 \text{ m}^3$ is considered; **d–i** Okada dislocation model. A N-S dislocation (opening of 1 m) of 5 km length located between 1 and 5 km depth. Two dipping angles are considered: **d–f** 90° and **g–i** 60°E (red line =

top of the dislocation). Left panels correspond to vertical displacements (positive when directed upwards) with black arrows indicating the horizontal displacements. Middle and right panels correspond to the E-W and N-S components of the horizontal displacement, respectively (positive when oriented towards the East and the North, respectively)

6.1 Signals Related to Magma Storage

The pressurization/depressurization of a magma reservoir induces stress changes in the host rocks causing in response displacements at the volcano's surface. The Mogi analytical expression (Mogi 1958) models the perturbation induced by a pressurized point source embedded in an elastic half-space. It provides a simple relationship between the depth H and the volume change ΔV of the source and surface displacements both horizontally U_r and vertically U_z (Eqs. 1 and 2).

$$U_r(r) = \frac{\Delta V(1-\nu)}{\pi} \frac{r}{(H^2 + r^2)^{\frac{3}{2}}} \quad (2)$$

$$U_z(r) = \frac{\Delta V(1-\nu)}{\pi} \frac{H}{(H^2 + r^2)^{\frac{3}{2}}} \quad (3)$$

with r being the radial distance from the point on the surface just above the source and ν the Poisson's ratio.

Figure 11a-c shows the vertical displacement and the horizontal (E-W and N-S) displacement field induced by a Mogi source located at 3 km depth with a volume change of $20 \times 10^6 \text{ m}^3$. Vertical surface displacement is maximum right above the center of the source and decreases rapidly with the radial distance. Horizontal surface displacement is distributed radially from the center of the source (black arrows in Fig. 11a). Due to the polar orbit of radar satellites, InSAR measurements in the line-of-sight will be more

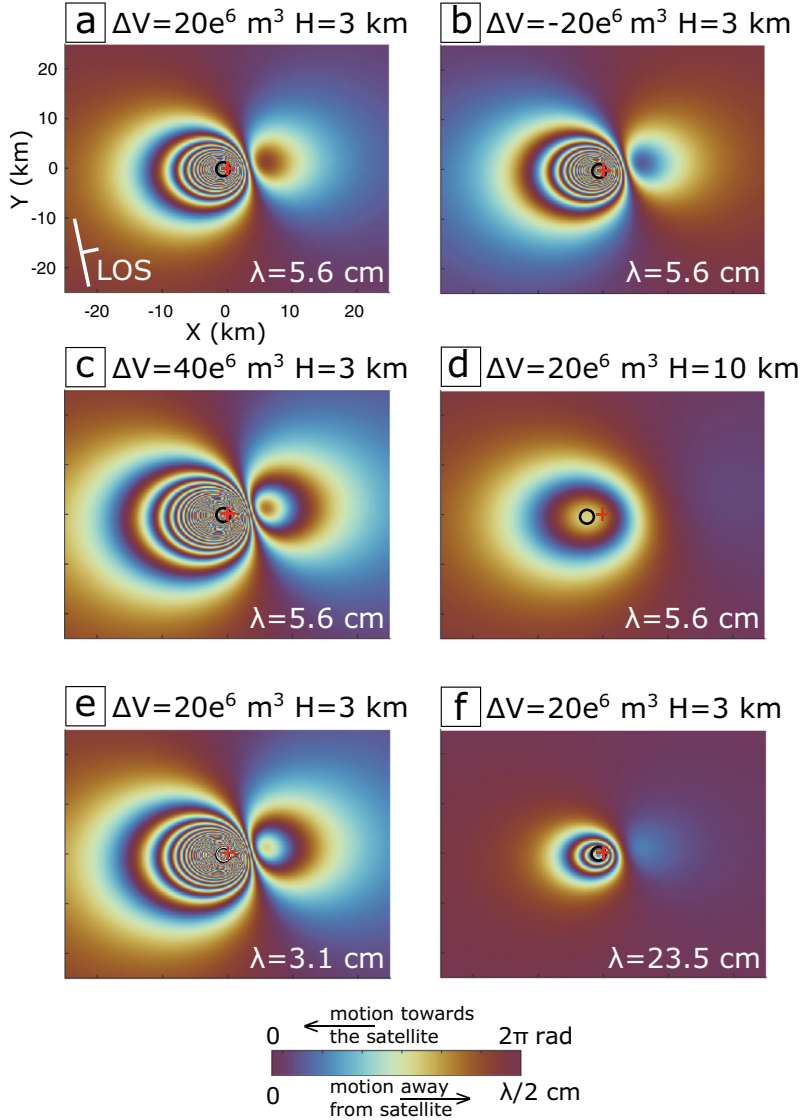


Fig. 12 Series of ascending wrapped geocoded interferograms showing the patterns of surface displacement induced by a Mogi source. Heading and incidence angles of the satellite are -12 and 40° , respectively. Red crosses correspond to the X-Y location of the source where the vertical displacement is maximum at the surface and black circles represent the location of the maximum LOS displacement.

a C-band interferogram induced by a Mogi model with a volume change of $20 \times 10^6 \text{ m}^3$ and reservoir's depth of 3 km; **b** Volume change of $-20 \times 10^6 \text{ m}^3$ and depth of 3 km; **c** Volume change of $40 \times 10^6 \text{ m}^3$ and depth of 3 km; **d** Volume change of $20 \times 10^6 \text{ m}^3$ and depth of 10 km; **e** Same model as (a) acquired in X-band; **f** Same model as (a) acquired in L-band

sensitive to vertical and E-W displacements (Fig. 11a, b).

Figure 12 shows an example of a synthetic ascending wrapped geocoded interferogram considering a C-band radar (i.e. $\lambda = 5.6 \text{ cm}$) and simulating the signal induced by a Mogi source located at 3 km depth with a positive volume

change of $20 \times 10^6 \text{ m}^3$. This case will be referred as the “reference case”. The pattern is composed of two ellipsoidal lobes of displacement. The western lobe shows a high number of fringes from 0 (blue) to 2π (red) (~ 16) with a phase decrease from the periphery to the center of the signal. It

corresponds to a phase change of -100 rad and a maximum displacement towards the satellite of $+35$ cm. Due to the SAR geometry, there is a horizontal shift (towards the West for ascending orbit) between the location of the maximum vertical displacement (red cross) and the location of the maximum displacement in the line-of-sight (LOS) (black circle). The eastern lobe shows less than one fringe. The motion is opposite to the western lobe with a phase increase from the periphery to the center. It corresponds to a phase change of 5.5 rad and a maximum displacement away from the satellite of -2 cm. This occurs in an area where the radial horizontal component of the displacement dominates compared to the vertical one and is directed towards the East (away from the satellite in the ascending orbit). The Fig. 12b shows the same model as Fig. 12a but with a negative volume change of $-20 \times 10^6 \text{ m}^3$. The only difference with the reference case is a shift in the direction of the motion with a phase increase for the western lobe and a phase decrease for the eastern lobe.

The Fig. 12c shows the same model as Fig. 12a but with a volume change of $40 \times 10^6 \text{ m}^3$. The difference with the reference case is an increase by a factor of two of the number of fringes for both lobes. The Fig. 12d is the same model as Fig. 12a with a reservoir depth of 10 km. An increase of the reservoir's depth induces a large reduction in the amplitude of displacement resulting in a decrease of the number of fringes by a factor of ~ 10 . In addition, vertical displacement dominates over horizontal displacement, and only one displacement lobe remains. The wavelength of the signal becomes larger for a deep reservoir than for a shallow reservoir. As a result, the horizontal shift increases between the location of the maximum LOS displacement and the location of the maximum vertical displacement.

Figure 12e and f show the same displacement signal as Fig. 12a, but if acquired by sensors at different wavelengths: (e) X-band sensor ($\lambda = 3.1$ cm) and (f) L-band sensor ($\lambda = 23.5$ cm). This only affects the number of fringes, with an increase by a factor of 1.8 for X-band and a reduction by a factor of ~ 4 for L-band. Therefore, the L-band radar sensor is more suitable than the C-band/X-band sensors for detecting a strong displacement gradient. Indeed, strong gradient results in a high frequency of fringes in wrapped interferograms

acquired with short-wavelength sensors. In the areas where the phase gradient exceeds π between two neighbouring pixels, phase aliasing occurs, resulting in a loss of information (see center of the Fig. 12e and Sect. 3.3).

Figure 13 shows the descending signals associated with the four models discussed in Fig. 12. There is no significant difference in the pattern of deformation to be discussed as all the descending signals are vertical mirror of the ascending ones. Note that the maximum displacement in the LOS is not shifted to the same side with respect to the source position, which means that there is a clear shift in the position of the maximum displacement in the LOS for ascending and descending interferograms.

6.2 Signals Related to Magma Propagation

Magma propagation from the reservoir to the surface occurs through planar intrusions and is usually modelled by dislocation models. The Okada analytical solution Okada (1985) provides a relationship between the geometry and the opening of the dislocation and the surface displacements considering an elastic half-space medium. Figure 11d–f shows the vertical and the horizontal displacements induced by a Okada model with a length of 5 km located between 1 and 5 km depth. The dislocation is vertical (dip of 90°) and oriented N-S (strike of 0°). Opening occurs in the direction perpendicular to the strike (e.g. E-W direction) and is fixed to 1 m in this example. The vertical surface displacements induced are negative (directed downwards) above the intrusion and positive (directed upwards) with two lobes of uplift at each side of the dislocation. In this configuration, the horizontal surface displacement is dominated by the E-W component (black arrows in Fig. 11d) with maximum displacement around 0.3 m. As a result, InSAR method will be less adequate for tracking horizontal displacements in the case where the dislocation is oriented along the E-W direction (i.e. strike of 90°). For dislocations with a dip angle less than 90° , a disymmetry will occur in the amplitude of the different lobes of

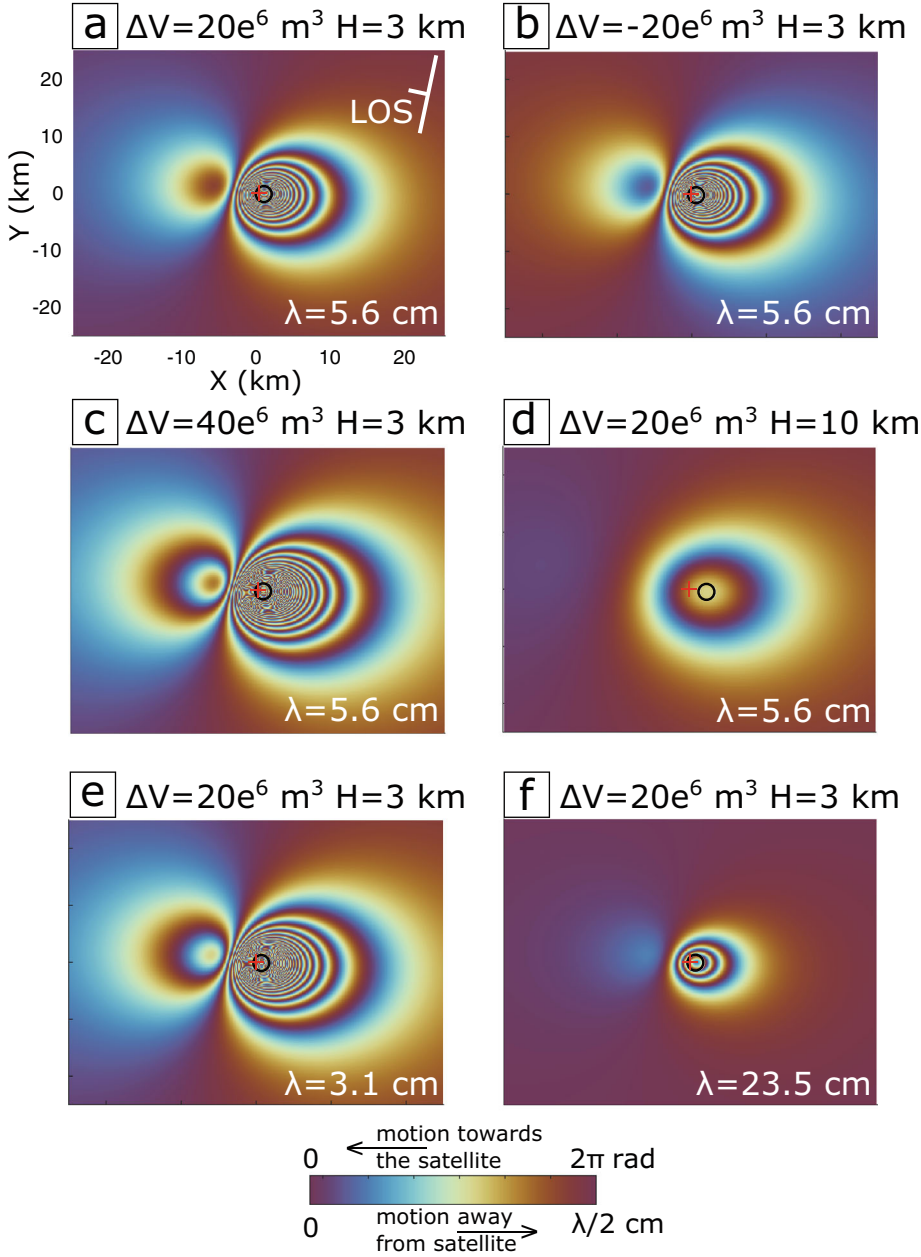


Fig. 13 Series of descending wrapped geocoded interferograms showing the patterns of deformation induced by a Mogi source. Heading and incidence angles of the satellite are 192 and 40°, respectively. Red crosses correspond to the X-Y location of the source where the vertical displacement is maximum at the surface and black circles represent the location of the maximum LOS displacement.

a C-band interferogram induced by a Mogi model with a volume change of $20 \times 10^6 \text{ m}^3$ and reservoir's depth of 3 km; **b** Volume change of $-20 \times 10^6 \text{ m}^3$ and depth of 3 km; **c** Volume change of $40 \times 10^6 \text{ m}^3$ and depth of 3 km; **d** Volume change of $20 \times 10^6 \text{ m}^3$ and depth of 10 km; **e** Same model as (a) acquired in X-band; **f** Same model as (a) acquired in L-band

displacements. Figure 11g–h shows the induced vertical and horizontal surface displacements for the same Okada model as Fig. 11g–h but for a dip

of 60°E. In this configuration, the amplitude of the eastern lobes (located above the dyke) is much

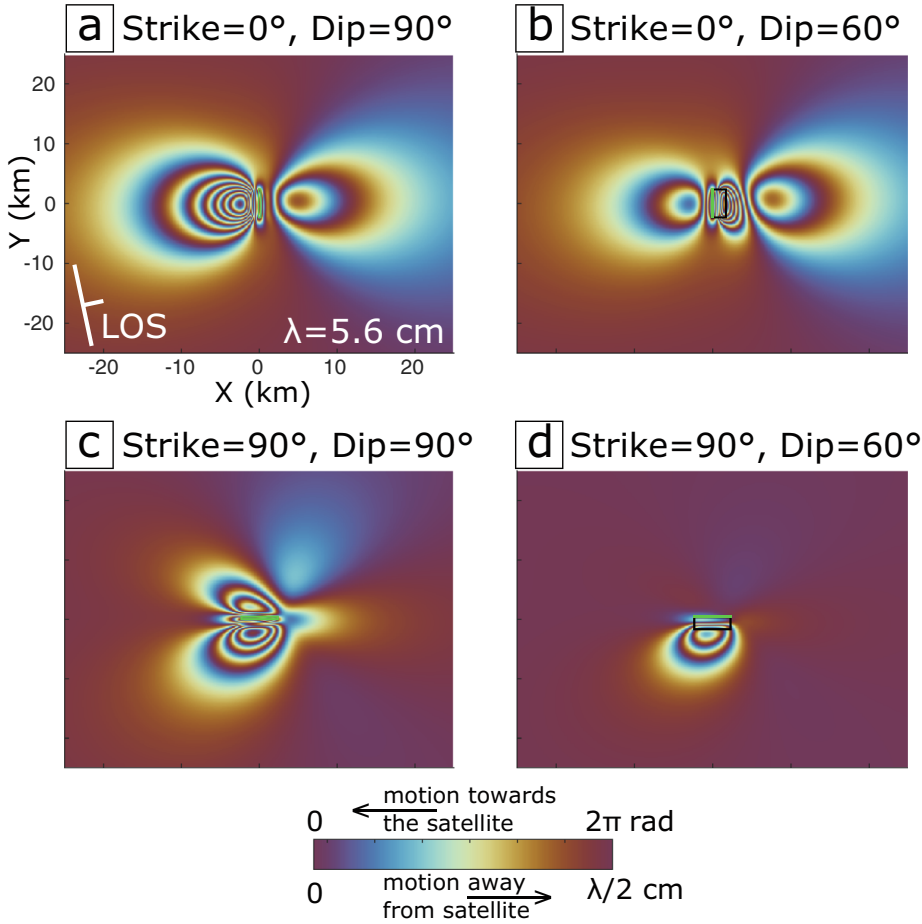


Fig. 14 Series of C-band ascending wrapped geocoded interferograms showing the patterns of deformation induced by an Okada dislocation source of 5 km length located between 1 and 5 km depth. Dislocation's opening is constant and fixed to 1 m. Heading and incidence angles of the satellite are -12 and 40° , respectively. Rectangle

indicates the trace of the dislocation (green line = top of dislocation). **a** model with a strike of 0° and a dip of 90° ; **b** model with a strike of 0° and a dip of 60° E; **c** model with a strike of 90° and a dip of 90° ; **d** model with a strike of 90° and a dip of 60° S

larger than the one of the western lobes for both vertical and horizontal displacements.

Figure 14a shows the ascending C-band wrapped interferogram associated with the Okada dislocation source shown in Fig. 11d-f. This case will be referred as the “reference case”. The pattern is composed of 3 ellipsoidal lobes of deformation. The western lobe shows ~ 7 fringes corresponding to a phase decrease of -44 rad from the periphery to the center of the signal, this corresponds to a displacement towards the satellite resulting from the addition of the vertical upward displacement and the horizontal

westward displacement. The eastern lobe is in the opposite direction and corresponds to a phase increase of $+12.5$ rad (displacement away from the satellite and the horizontal eastward displacement dominates over the vertical upward displacement). In the middle, we observe a small lobe of phase increase associated with the negative vertical displacement above the dislocation shown in Fig. 11d. In the case the dip is reduced to 60° E (Fig. 14b), the amplitude of displacements on the western lobe is reduced whereas the pattern of the eastern lobe is similar. In addition, we can notice two lobes of displacements in the center: one similar to the previous case (phase

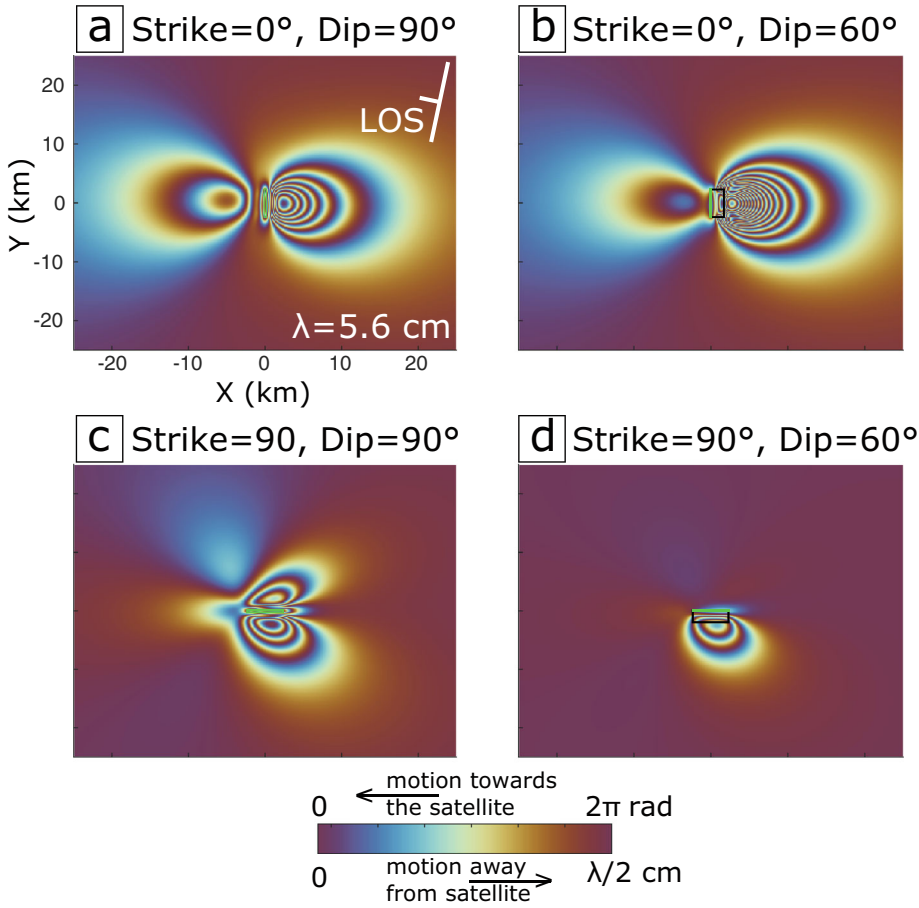


Fig. 15 Series of C-band descending wrapped interferograms showing the patterns of deformation induced by an Okada dislocation source of 5 km length located between 1 and 5 km depth. Dislocation's opening is constant and fixed to 1 m. Rectangle indicates the trace of the dislocation

(green line = top of dislocation). Heading and incidence angles of the satellite are 192 and 40°, respectively. **a** model with a strike of 0° and a dip of 90°; **b** model with a strike of 0° and a dip of 60°E; **c** model with a strike of 90° and a dip of 90°; **d** model with a strike of 90° and a dip of 60°S

increase) and another one of phase decrease. In the case the strike is E-W (Fig. 14c), the signal shows two lobes of phase decrease at each side of the dislocation (i.e. the northern and southern part). In the center, a small signal of phase increase is still present. In this configuration, the line-of-sight displacement is dominated by the vertical component. In the case of a strike of 90° and a dip of 60°S (Fig. 14d), the signal is the smallest of the four cases with only one lobe of displacements clearly visible in the southern part.

The Fig. 15 shows the descending signals associated with the four models discussed in Fig. 14. Descending signals are vertical mirror of the ascending ones, except the case of panel b)

with Strike=0° and Dip=60°E. In this scenario, the descending interferogram shows a clear asymmetry in the pattern with a maximum phase changes close to -100 rad from the periphery to the center in the eastern lobe and only +8 rad range in the western lobe. The difference of pattern with large displacements on the eastern lobe can be explained by the fact that for a dike dipping towards the East, the displacement upward and towards the East is enhanced on the eastern side of the dike resulting in a strong displacement towards the satellite for the descending track. For the ascending track, the mirror signal with highest displacements on the western lobe would be produced for a dislocation with a Dip=60°W.

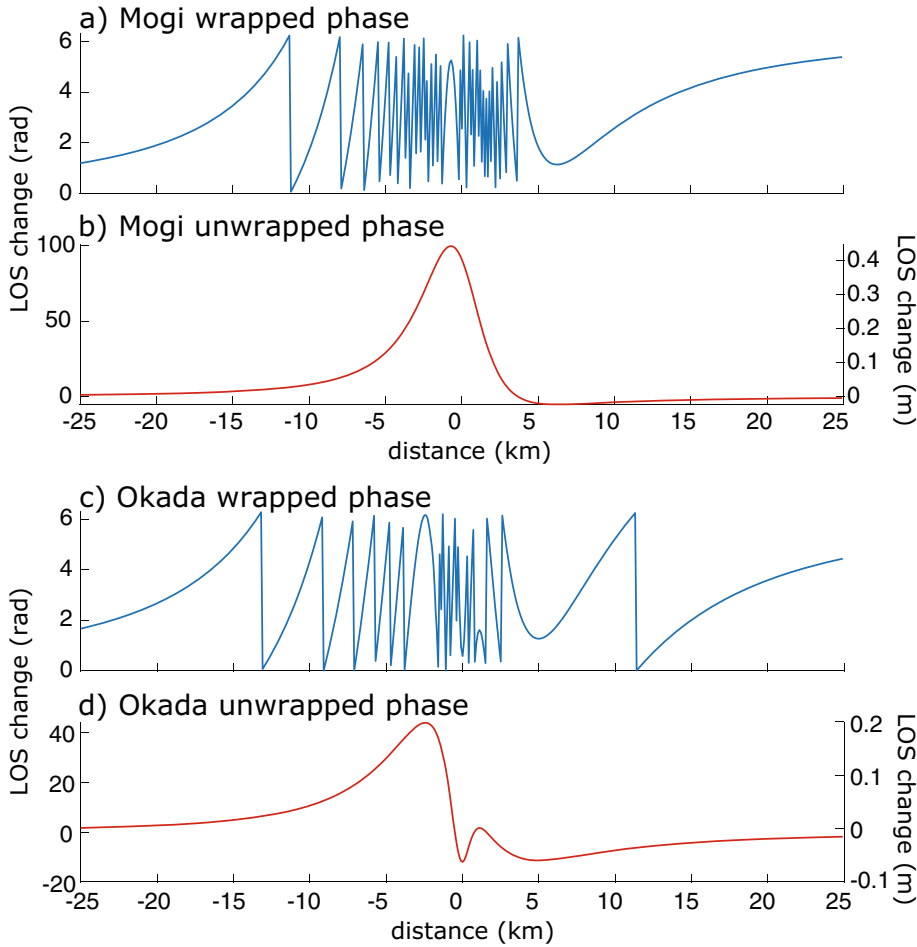


Fig. 16 Principle of phase unwrapping shown for two simulated signals of magmatic sources. **a, b** E-W profile (with $Y = 0$ km) of wrapped and unwrapped phase for the

Mogi reference case shown in Fig. 12a; **b, c** E-W profile (with $Y = 0$ km) of wrapped and unwrapped phase for the Okada reference case shown in Fig. 14a

We can now start to interpret the ascending interferogram shown in Fig. 5. There are two lobes of fringes located in the northern part of Enclos Fouqué, the western lobe with around 8 fringes corresponds to a displacement towards the satellite of a bit more than 20 cm, whereas the eastern one with around 4 fringes corresponds to a displacement away from the satellite around 10 cm. This signal is consistent with magma emplacement at depth in the northern part of the caldera, east of the crater. Considering only one geometry of acquisition it remains difficult to infer the geometry of this magmatic intrusion. Inversion of the intrusion shape is usually performed considering at least the ascending and descending track

either based on analytical solution as the Mogi and Okada models (e.g. Bagnardi and Hooper 2018) or numerical models (e.g. Fukushima et al. 2005). But before inversion can be performed it is usually required to convert the phase change measured with an ambiguity of 2π in a LOS continuous displacement as explained in Sect. 3.3.

Figure 16 illustrates the principle of unwrapping in 1D with examples of profiles of LOS changes associated with the simple analytical sources (Mogi and Okada) described above. In the panels (a) and (c) of Fig. 16, we observe high frequency of cycle between 0 and 2π related to the signal of ground displacement. The unwrapping step consists of summing all the individual cycles to produce the continuous field of LOS change

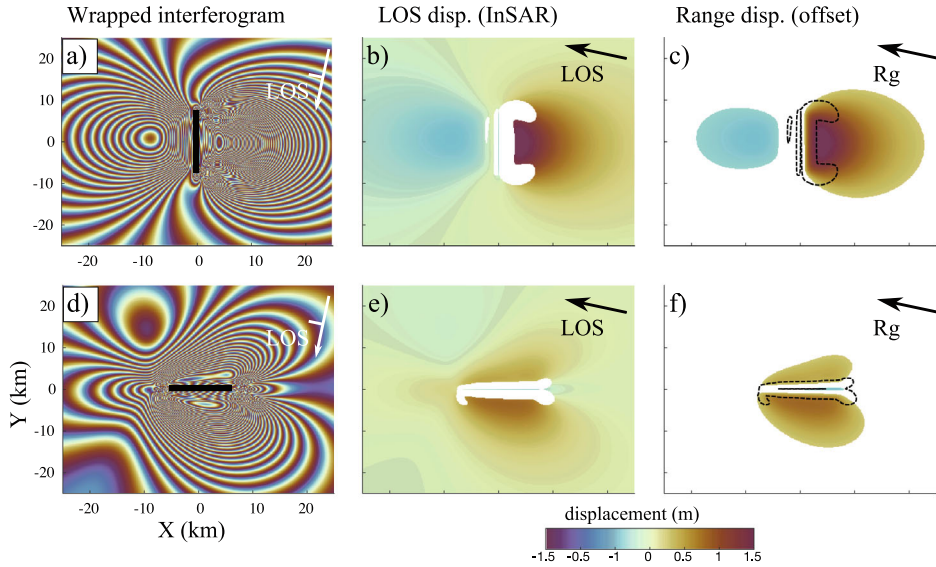


Fig. 17 Comparison of the displacement field retrieved by differential interferometry and pixel offset tracking. **a, d** Wrapped Sentinel-1 descending interferograms induced by the 5 m opening of a 15 km length vertical dislocation located between 1 and 10 km depth. Black rectangles indicate the projection of the dyke at the surface: Strike of 0° in **(a)** and 90° in **(d)**. **b, e** Corresponding LOS displacements retrieved by the method of differential inter-

ferometry. Phase changes exceeding π (radian) can not be detected (white area). **c, f** Corresponding range displacements retrieved by the method of pixel offset tracking. Displacement has to exceed 1/10 of the pixel spacing in the range direction to be detected. Here, this threshold is fixed to 30 cm, considering 3 m range resolution of Sentinel-1 raw data. Black dots outline the area that can not be detected by InSAR

(Fig. 16b,d). The corresponding phase changes in meter for the two examples are shown in the right y-axis of Fig. 16b,d, using $\lambda = 5.6$ cm (C-band).

Figure 17 illustrates once again how pixel offset tracking may complement InSAR measurements by providing information in the near field of magma intrusions, affected by a strong displacement gradient, especially for intrusions with Azimuth= 0° . Note that for the two examples considered in Fig. 17, the pixel offset tracking does not detect any displacements in the azimuth direction, as amplitude remains lower than 1.5 m (1/10 of the 15 m azimuth pixel ranging of the Sentinel-1 IW).

7 Real Time Monitoring

Despite the enormous opportunity that SAR data can represent for volcano monitoring, these data are so far largely underused in volcano observatories (Meyer et al. 2015). Historically, this could be due to the complexity of radar data, which makes it difficult to process and interpret compared to

optical imagery for example, its relatively low temporal resolution due to poor temporal sampling, and the latency of data access at the beginning. However, all these drawbacks have been largely overcome in recent years.

Consequently global efforts in favor of automation and near-real time production accelerated (Valade et al. 2019; Meyer et al. 2019; Lazecký et al. 2020; Morishita et al. 2020; Derauw et al. 2020) together with the development of methods for automatically detecting and extracting displacement signals (Gaddes et al. 2018, 2019; Albino et al. 2020; Anantrasirichai et al. 2018, 2019) and for predicting the evolution of ground displacements (Bato et al. 2017).

We can acknowledge that SAR imagery has provided key information in several episodes of volcanic unrest or eruptions in the last decade. During the Merapi eruption in 2010, high-resolution amplitude imagery was used to define evacuation zones, thus avoiding loss of life (Pallister et al. 2013). During the 2017 seismic

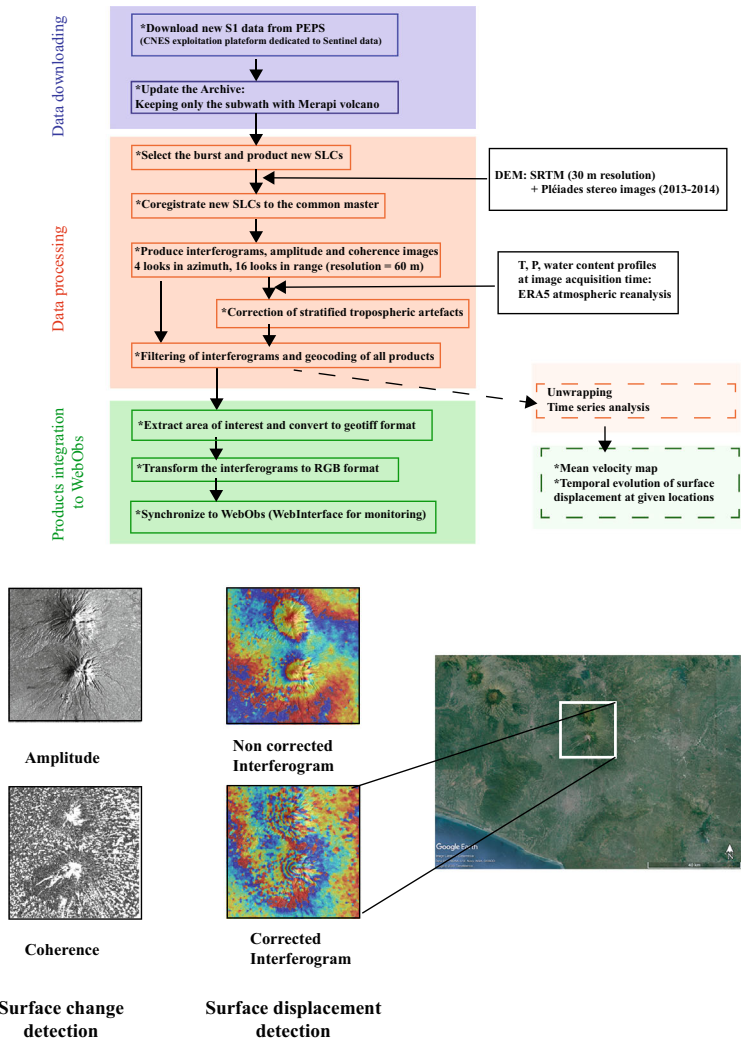


Fig. 18 Flowchart of Sentinel-1 data integration into the monitoring web-based system at BPPTKG in charge of Merapi volcano monitoring in Yogyakarta, Indonesia. The bottom part shows the various products available online in

WebObs, an integrated web-based system for monitoring and networks management (Beauducel et al. 2020), with the footprint of the area observed

crisis at Agung volcano, Sentinel-1 interferograms were processed routinely and corrected from atmospheric noise when weather-based models became available. Although a broad signal in the NE flank of the volcano has been noticed in some descending interferograms prior to the November eruption, the presence of a deformation signal induced by the propagation of a dyke was confirmed retrospectively only after a detailed analysis of the ascending and descending InSAR time series (Albino et al. 2019,

2020). More recently, during the Taal eruption in January 2020, Sentinel-1 data were used to track the progress of a tens of kilometres long magma intrusion just below the surface in real time (Bato et al. 2021). In this case, the pre-eruptive inflation was also revealed a posteriori because no one had carefully studied the InSAR time series prior to the eruptive event.

In each of these three scenarii, the satellite data were processed and then provided to the volcano observatories by external collaborators, which can sometimes delay the response during a crisis

event. To improve the near real-time monitoring of active volcanoes using radar interferometry by local observatories, few important actions can be proposed:

- to develop and install automatic processing chains in volcano observatories that produce well-calibrated results from satellite data that can be jointly interpreted with field data.

- to propose online/on-site courses to staff working in volcano observatories to teach them how to access, process, and interpret SAR data (e.g. Watson et al. 2023).

These actions must be done in the long-term and in quiet periods where volcano is not active, as it becomes almost impossible to do so in periods of crisis. There are few observatories where this effort has been made, such as, for instance, the Observatoire Volcanologique du Piton de la Fournaise (OPVF) (Richter and Froger 2020) or the BPPTKG, which is part of the CVGHM in charge of monitoring Merapi volcano in Indonesia (see Fig. 18).

8 Conclusion, Future and Perspectives

By allowing the detection and quantification of long-term uplift at Earth's surface that signals magma storage at depth, InSAR measurements have enormous potential for volcano monitoring and there is currently a global effort of the scientific community to take advantage of this opportunity.

In addition, international space agencies continue the development and the operation of new Earth-observing missions that will be crucial for better monitoring and managing future disasters to come. In the next decades (2022–2030), new satellite radar missions with L-band sensors have been confirmed such as NISAR (NASA/ISRO) and ALOS-4 (JAXA) whereas other missions such as TanDEM-L (DLR) have been considered. For example, the NISAR mission will deliver L-band radar images worldwide in open-access. Such new datasets will be complementary of the Sentinel-1 imagery (C-band) and even more suitable to detect

ground deformation signals on active volcanoes covered by dense vegetation.

Finally, all these radar datasets should be used in conjunction with other satellite imagery such as optical data acquired in stereo mode allowing quantification of erupted volumes and magma flow in near-real time (Pedersen et al. 2022) or thermal imagery giving insight into the evolution of thermal anomalies over time (Girona et al. 2021). They should also be integrated as much as possible with existing ground-based measurements, in particular with GNSS data, in order to take advantage of the complementarity between the wide spatial coverage of InSAR data and the high temporal resolution of GNSS measurements as shown for instance by Smittarello et al. (2019).

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Detection and Location of Volcano-Tectonic Earthquakes

Guoqing Lin

Abstract

Volcanic eruptions are one of the most hazardous natural disasters on Earth. With the increasing rate of development of areas on and around volcanoes, more people and property are at risk of volcanic activity. Thankfully, volcanoes exhibit precursory unrest that, if detected and analyzed in time, it may be possible to anticipate eruptions and forewarn communities at risk. Volcanic eruptions often occur along with earthquakes and/or tremor. Seismology, together with other geophysical and geochemical studies, can help our understanding of the eruption process because seismicity within a volcanic system can provide evidence of an impending eruption or sources for tracking the movement of magma. One of the various types of seismic signals produced are volcano-tectonic earthquakes, which are so named because they share features with typical tectonic earthquakes, which allow them to be detected and located using similar approaches in automatic processing systems.

High-precision earthquake relocations can be obtained by applying more sophisticated techniques, including waveform cross-correlation, though this is not routinely applied to volcanic areas.

1 Introduction

Volcanic eruptions are a natural hazard that produces many kinds of destructive phenomena, such as lava flows, debris avalanches, gas emissions, and airborne ash clouds. Though depending on the specific volcanoes and observatories, active volcanoes are commonly defined as those that have erupted at least once within the last $\sim 10,000$ years. By this definition, there are currently about 1,350 active volcanoes in the world. Figure 1 shows all the Holocene volcanoes according to the Global Volcanism Program (2013). About 400 of these volcanoes have erupted since 1960. Every year, about 60 volcanoes erupt in the world according to the Smithsonian Institution catalog of historical eruptions. Before and during a magmatic eruption/intrusion, magma and volcanic gas force their way through underground structures, which may lead to a number of detectable precursors, including seismic unrest, ground deformation and gas emission. One of the most commonly used and important monitoring tools are seismometers, sensitive instruments that generate electrical currents

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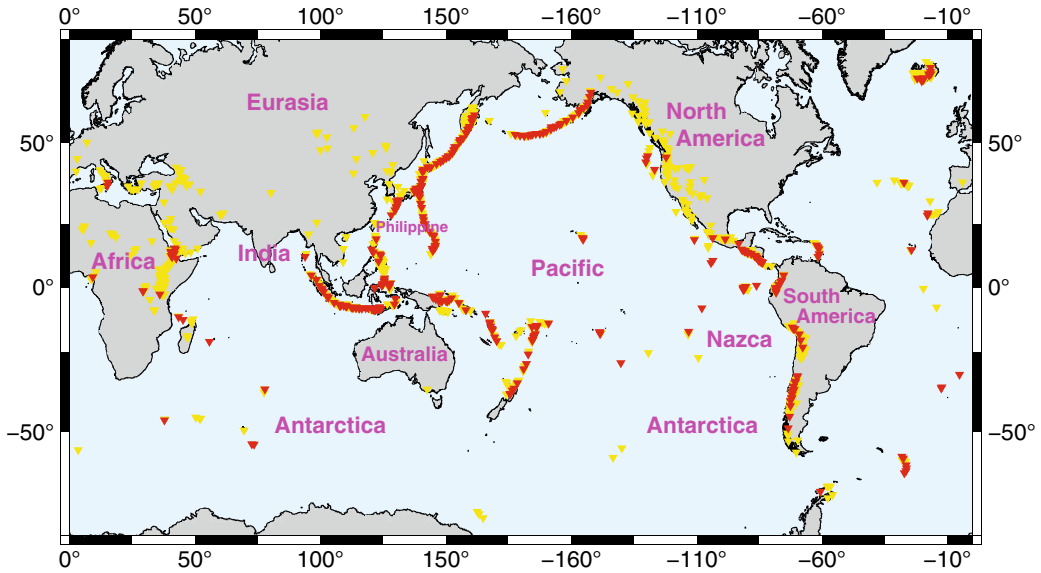


Fig. 1 Global distribution of Holocene volcanoes according to the Global Volcanism Program (2013, last accessed in June 2022). Red inverted triangles represent those with last known eruptions since 1960

in response to ground vibrations due to any natural (e.g., earthquakes, wind, and ocean waves) and anthropogenic (e.g., cars, helicopters, livestock, and blasting) sources. The majority of the active volcanoes are monitored by regional/local observatories (Fig. 2), most of which were founded or became permanent in 1980–1990s.

Seismic monitoring is vital for accurate and timely information used in hazard mitigation from earthquakes and volcanic eruptions (Pallister and McNutt 2015). A digital seismograph is composed of a sensor (seismometer) and a recorder. A permanent seismometer is usually buried at shallow depths (1–2 m) beneath the ground surface, measuring the ground motions on which it rests and converting them into electric signals. Borehole seismometers, installed up to 250 m below ground, are also used to monitor volcanoes (e.g., Yellowstone), and can detect and locate much smaller seismic signals. The recorder produces a seismogram that shows amplitudes of ground velocity (sometimes displacement) as a function of time. The electronics and power supplies are often stored in ground housings. The recorded data are then transmitted in real time or near-real time to the computers at the monitoring observatories for further processing. Scientists at the

observatories monitor changes in seismicity patterns and rates to track subsurface processes that may be related to magmatic activity and use these data to alert the community and other governmental agencies for public safety or pursue research to advance scientific understanding of volcanoes. For active volcanos, six or more seismic stations are recommended for effective seismic monitoring within ~ 20 km from the volcanic center or active vent (Moran et al. 2008) to constrain shallow earthquake locations (and volcanic edifices and crustal structure) and to produce a more complete earthquake catalog. For highly active volcanoes (e.g., Kīlauea volcano in Hawai‘i), the number of close stations are recommended to be 12 or more (Moran et al. 2008). During the deployment, the goal of the monitoring needs to be taken into account, such as local/regional monitoring, depth control, and azimuthal coverage. Permanent seismic deployments at active volcanoes can be challenging and are limited by local terrain (accessibility/safety), telemetry conditions (power/noise), and magmatic activity. Nevertheless, even one seismic station can be beneficial for the monitoring and understanding of a magmatic system (Sparks et al. 2012). Signals recorded by a nearby seismic station can be used for event counting

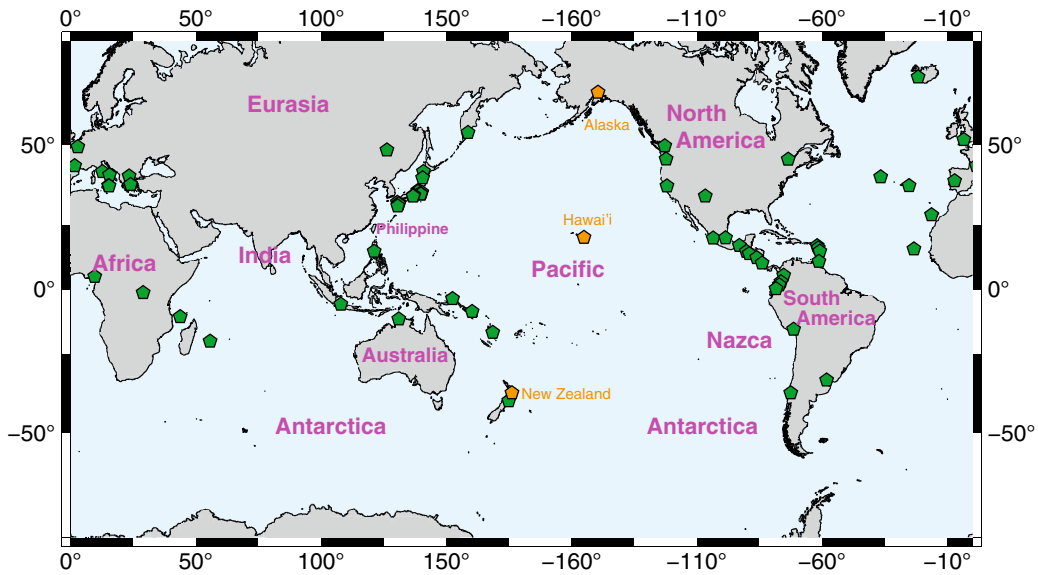


Fig. 2 Volcano observatories from the World Organization of Volcano Observatories (<https://wovo.iavceivolcano.org/observatories>). Locations for the three case studies, Hawai'i, Alaska and New Zealand, are shown by the orange pentagons

(increase of seismic activity is often one of the precursory signals before volcano eruptions), calculation of the differential time between shear-wave (S) and primary-wave (P) arrival time (for estimating epicentral distance), and identification of event type changes (Zobin 2012). If more stations are available, then the recorded signals can be used to distinguish between volcanic and non-volcanic processes and improve accuracies of earthquake locations.

2 Volcano-Tectonic Earthquakes

At volcanoes, multiple processes produce seismic signals, which are often distinctive and reflect the underlying physics of the source process. Events recorded at active volcanoes can be classified based either on the shape of seismogram (e.g., amplitude, frequency, and duration) or on the corresponding physical mechanisms (Ohminato et al. 1998; Wassermann 2002; McNutt 2005; Roman & Cashman 2006; Salvage et al. 2017). The high-frequency (5–20 Hz) events are often referred to as volcano-tectonic (VT) earthquakes. Another type of event that has drawn great attention in the volcano community is low frequency

events, including low-frequency or long-period (LP, 0.5–5 Hz), VLP (0.01–0.5 Hz), tornillo, and tremor (McNutt 1996; Wassermann 2002; McNutt et al. 2015). These long-period events are commonly associated with magma/fluid/gas movement within a magmatic system and can inform the state of the volcano. Figure 3 shows raw waveforms at six common seismic stations for a VT earthquake and an LP event identified by the Hawaiian Volcano Observatory. Both events are located at about 2.5 km depth below mean sea level within Kīlauea's summit caldera, but manifest distinct frequency dominance. Note that in this chapter all depths are relative to mean sea level unless otherwise stated. Because seismic stations can record any ground motions regardless of their sources, there are also signals due to surface events, including explosions, rockfalls/pyroclastic flows, icequakes, traffic, and regional/teleseismic events.

The focus of this chapter is on VT earthquakes. As the name indicates, VT earthquakes are tectonic earthquakes near or at a volcano and sometimes reflect the interaction of two general geological processes: the magma movement and tectonic activity. They can occur within and below the volcanic edifice. These earthquakes

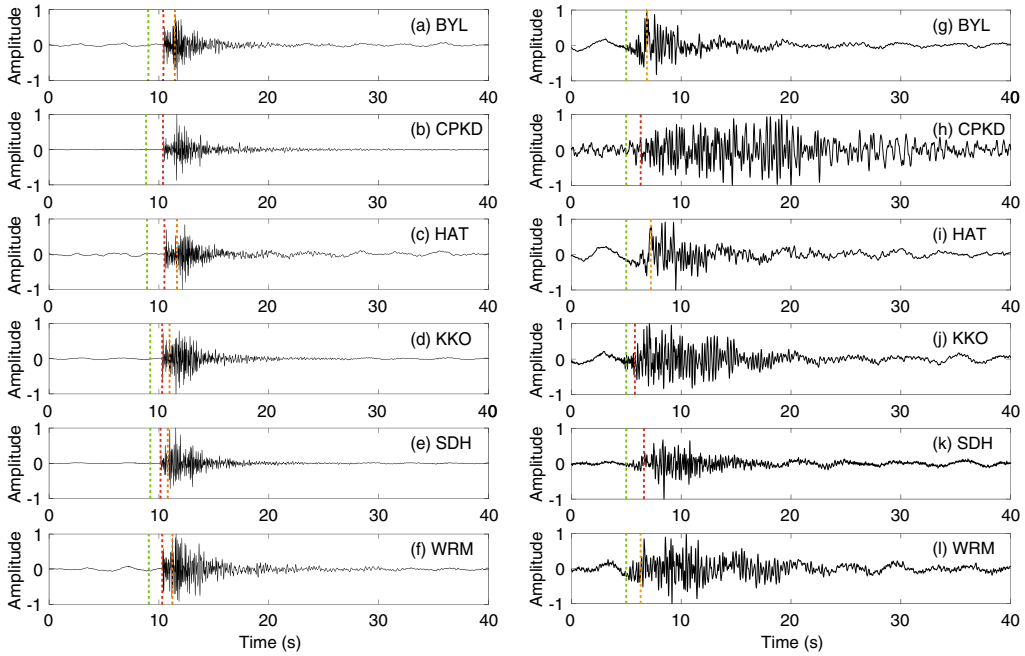


Fig. 3 Raw waveforms with normalized amplitudes recorded at the vertical component of six common seismic stations for a VT earthquake (left) and an LP event (right) identified in the Hawaiian Volcano Observatory catalog. Both events are about magnitude 1.8 and located at

~2.5 km depth below mean sea level within Kīlauea’s summit caldera. Dotted green, red, and orange vertical lines denote the origin time, P-, and S-arrival of each event, respectively

are very like tectonic earthquakes because they are dominantly due to fault slip, but mainly forced by volcanic stresses instead of tectonic stresses (White et al. 2019). VT earthquakes are sometimes separated into deep (A-type) and shallow (B-type) events based on their depths (Wassermann 2002), but this classification has not been commonly applied due to uncertainties in earthquake depths. Regardless, deep events, originated from a deeper part (usually below ~2 km) of the magmatic system, often have abrupt P- and S-arrivals and are difficult to distinguish from regular tectonic earthquakes. Shallow events are usually at depths of < 2 km near the active crater and often have emergent P-wave and unclear S-onsets. VT earthquake swarms can occur from the summit area to hundreds of kilometers away. Studies have shown that VT earthquake swarms tend to have an anomalously large number of small events compared to the usual seismic sequences (e.g., McNutt 2005). Although

VT earthquakes typically occur in more noisy environments and have smaller magnitudes, traditional seismological research can be conducted on them because of their similarities with the typical tectonic earthquakes (e.g., those in California), such as event detection, high-accuracy location, tomography, focal solution, and moment tensor (e.g., Chouet 1996; Wassermann 2002; Chouet 2003).

3 Monitoring System and VT Earthquake Detection

With the continuing development of computers and advancement of technology, modern monitoring of volcanoes is based on automatic processing systems. Commonly used monitoring systems include IASPEI (International Association of Seismology and Physics of the Earth’s Interior) acquisition system (Lee et al. 1988), Earthworm

modules (Johnson 1995), SeisComp3 (Helmholtz Centre Potsdam 2008; Olivieri and Clinton 2012), Antelope, Hydra (Patton et al. 2016), and SEISAN (Havskov et al. 2020). Most of these systems are composed of detection-association-location processing. The real-time seismic data are transmitted to the reception computers at central observatories and processed automatically. Different observatories have distinct procedures. At some observatories or agencies the data are reviewed by analysts. Others release the automatically acquired earthquake information for public record and only confirm the results for special earthquakes.

The detection of VT earthquakes is similar to that for regular tectonic earthquakes. The central computer at the corresponding observatory is set up to look for signals that are distinct from the recordings immediately preceding them, usually referred to as the background activity. Those whose amplitudes exceed the background level could be associated with an earthquake. Techniques similar to the short-time-average/long-time-average (STA/LTA) method (Withers et al. 1998; Trnkoczy 2009) are commonly applied. If a certain number of predefined criteria or thresholds, such as STA duration, LTA duration, and STA/LTA ratio, are satisfied, then a detection is deemed significant. If the same detection occurs at several stations, then a seismic event is identified. Recently, the template matching technique has been applied to volcanic areas for earthquake detection to complement the network catalog (e.g., Shelly and Thelen Shelly and Thelen 2019). A difference between a regular seismic and a volcanic monitoring system is event classification. Volcanic event triggers are sometimes classified as a VT earthquake or an LP event or other types.

4 VT Earthquake Location

Once an event is detected, its location can be refined by the seismic recordings from multiple stations. Location or hypocenter (epicenter, depth and origin time) is one of the most important parameters for an earthquake. An accurate catalog of earthquake locations is one of the most funda-

mental and important monitoring tasks at volcano observatories. One of the most distinguishable differences between VT earthquakes and other types of events is their clear, impulsive P- and sometime S-arrivals (Fig. 3). Because of the availability of the first arrivals, VT earthquakes can be located in the same way as typical tectonic earthquakes. In old days, the location procedure was based on graphics and manual efforts. Since the 1960s, with increases in the number of seismic stations (both globally and locally) and the development of modern computers, the location process has ever since migrated to real-time or near-real-time computer-based procedures, in which the times of P and S wave arrivals are inverted against seismic velocity models of the earth structure to yield the best location for the event. With more arrivals coming in, the event location may be adjusted. Commonly applied earthquake location software at monitoring observatories include LOCSAT (Nagy 1996), Hypoellipse (Lahr 1999), Hypoinverse (Klein 1978, 2014), and NonLinLoc (Lomax et al. 2000). These approaches locate one earthquake at a time, without information from any other events, and are often referred to as “single-event location” methods.

Accurate earthquake locations are fundamental parameters necessary for studies of earthquake physics, fault orientations and crustal deformation. For active volcanoes, they are essential for characterizing magmatic pathways and identifying magma migration. Based on the location information provided by the monitoring observatories, researchers apply more sophisticated methods to improve accuracies in earthquake locations. Earthquake location errors can be affected by many factors, including the number of recording stations, distribution or azimuthal coverage of the network, and errors in travel times. Travel time data typically are noisy and contain both random and systematic errors. The random errors are mainly the picking errors, during either automatic or manual picking. The systematic errors often result from the deviations of the velocity model used in calculations from the real structure. This results in two aspects in earthquake location: one is absolute location, the other is relative location. Figure 4 illustrates the

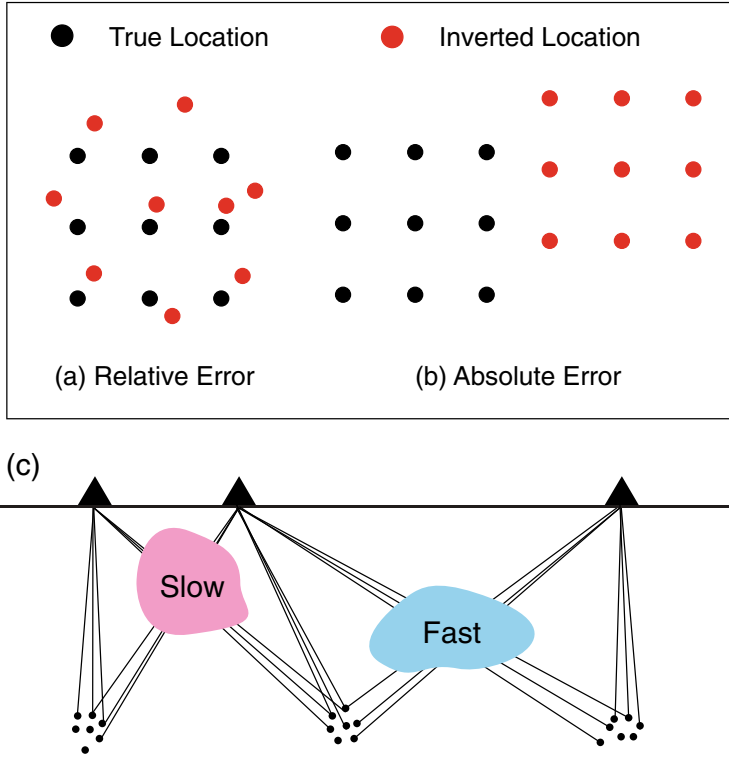


Fig. 4 a, b Illustration of relative versus absolute location errors. c Distributed seismicity in general 3-D structure. The pink and blue shades represent the slow and fast

velocity anomalies in real structure. In this case, the travel time corrections to each station vary as a function of source position but are highly correlated among nearby events

differences between these two types of location errors. If the events are distorted but not shifted from the true location, then this cluster has good absolute locations, but bad relative locations (Fig. 4a). While if the cluster is displaced from their true location, but not distorted, then the cluster has good relative locations but bad absolute locations (Fig. 4b). Absolute location error is due to our limited knowledge of three-dimensional (3-D) velocity structure, so 3-D velocity models are often inverted to improve absolute location accuracy. This is usually done by simultaneously solving for earthquake location and 3-D velocity models for local tomography. For relative location improvements, many different techniques have been presented to improve relative locations for both small compact event clusters and distributed seismicity (Fig. 4c). These methods are based on one-dimensional (1-D) models and attempt to correct for the

systematic biases in arrival times caused by 3-D velocity variations without actually solving for the velocity structure itself. These new methods include joint epicenter determination, station terms, and master event locations (e.g., Douglas 1967; Evernden 1969; Lilwall and Douglas 1970; Frohlich 1979; Jordan and Sverdrup 1981; Smith 1982; Pavlis and Booker 1983; Viret et al. 1984; Pujol 1988). The mostly commonly used ones, the double-difference approach (Waldhauser and Ellsworth 2000, 2002) and the source-specific station terms (Richards-Dinger and Shearer 2000; Lin and Shearer 2005, 2006) represent generalizations of these methods from isolated clusters of events to distributed seismicity.

Relative locations can be greatly improved using waveform cross-correlation data to produce a dramatic sharpening of seismicity patterns compared to standard methods. A key benefit of waveform cross-correlation is more precise timing of

P and *S* arrivals. The waveforms of nearby earthquakes recorded at the same station are often similar enough that waveform cross-correlation can be used to obtain much more precise differential times than can be picked on individual seismograms. With the development of modern computers and recent high-performance computing, waveform cross-correlation has become an increasingly important tool for improving relative earthquake locations, characterizing event similarity and studying earthquake source properties (e.g., Poupinet et al. 1984; Got et al. 1994; Nadeau et al. 1995; Gillard et al. 1996; Shearer 1998; Rubin et al. 1999; Waldhauser et al. 1999; Astiz et al. 2000; Shearer et al. 2003; Rowe et al. 2004; Hauksson and Shearer 2005; Schaff and Waldhauser 2005; Lin et al. 2007; Lin and Shearer 2007; Lin et al. 2008; Waldhauser 2009; Lin and Shearer 2009; Lin and Thurber 2012; Matoza et al. 2013; Lin et al. 2014, 2015; Lin and Okubo 2016; Lin 2020; Shelly 2020; Lin et al. 2021, 2022). The more precise times provided by waveform cross-correlation make possible relative location accuracy of tens of meters or less within individual similar event clusters, permitting detailed imaging of small-scale structure. However, waveform cross-correlation is not yet implemented routinely for network data owing to its greater computational requirements compared to standard processing based on individual phase picks. In the following sections, earthquake locations are referred to as 1-D, 3-D, and cross-correlation locations if they are obtained by using a 1-D velocity model, 3-D velocity model, and waveform cross-correlation data, respectively.

5 Case Studies

In this section, results from VT earthquake monitoring at three observatories are used as case studies. Each of their monitored areas has experienced at least one volcanic eruption in the past three years (as of June 2022). For each observatory, I start with a brief review of the monitoring history and show earthquake location and relocation studies for some representative volcanoes. Due to the enormous number of earthquakes in each region,

I only use one year of earthquake data in the examples.

5.1 Hawai'i

The Island of Hawai'i was formed by volcanic eruptions, and consists of several large volcanoes, including the world's largest volcano, Mauna Loa, and the world's largest active volcanic crater, Kīlauea (Fig. 5a). Before its 2022 eruption, Mauna Loa had erupted 33 times since its first well-documented historical eruption in 1843 (Trusdell 1995) and had gradually risen to more than 4 km above sea level. Its last eruption took place in 1984 and had intrusions in 2002–2005 and 2014–2020 (Amelung et al. 2007; Okubo and Wolfe 2008; Varugu and Amelung 2021). After its longest quiet period in recorded history since 1984, Mauna Loa erupted in November 2022. It is one of the 16 volcanoes identified by the International Association of Volcanology and Chemistry of the Earth's Interior as being worthy of particular study in light of its history of large, destructive eruptions and proximity to populated areas. Kīlauea, on the southern flank of Mauna Loa, is the youngest and southeasternmost volcano on the Island of Hawai'i. It had many eruptions in the summit area in the 1960–1970's (MacDonald et al. 1983). From 1983 to 2018, it had been continuously erupting from vents in the East Rift Zone (ERZ). A degassing vent opened within Halema'uma'u crater at Kīlauea's summit in March 2008. In 2018, Kīlauea experienced its largest Lower East Rift Zone (LERZ) eruption and caldera collapse in at least 200 years (Neal et al. 2018).

Hawai'i Island is one of the most densely monitored volcanic regions in the world and has been serving as a natural laboratory for studying the interactions between seismic and magmatic processes for the past few decades. The Hawaiian Volcano Observatory (HVO), administered by the U.S. Geological Survey (USGS), has been operating a seismic network since 1912 to monitor and investigate hazards from active volcanoes and earthquakes in Hawai'i. Okubo et al. (2014) detailed the history of the HVO seismic monitoring network and data processing

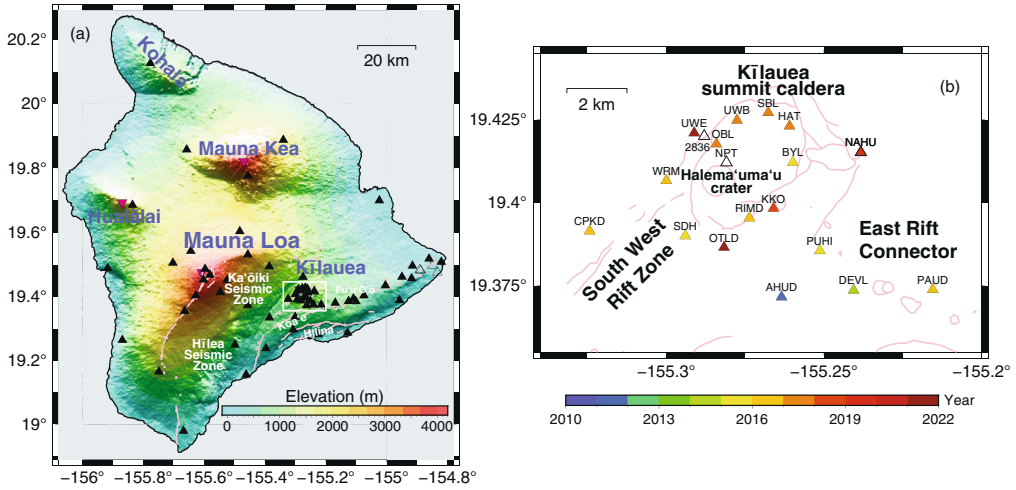


Fig. 5 Distribution of the Hawaiian Volcano Observatory (HVO) seismic stations. **a** On the entire island of Hawai‘i; and **b** Near Kilauea’s summit caldera and the East Rift Connector (Swanson et al. 2018). The white box in (a) shows the location of (b) on the island. Pink inverted trian-

gles in (a) represent the Holocene volcanoes. Stations that are operational at the time of writing (June 2022) are colored by their latest deployment or upgrade time and those lost during the 2018 Kilauea eruption are shown by open triangles in (b). Pink lines stand for fault traces

methods. Starting with 2 seismic instruments in 1912, HVO has experienced several periods of network growths and instrument upgrades. Modernization began in 1950 with a steady increase in the number of stations and components and development of microearthquake monitoring. In the mid-1960s, radio telemetry started gradually to replace cables for data transmission, which accelerated expansion of the network into new and remote areas. In 1966, HVO began to identify earthquake types beneath Kilauea’s summit region and added the “LP” classification to the HVO catalog (e.g., Okubo and Nakata 2003) in addition to “VT” earthquakes. However, given the amount of data and lack of resources, this has not been consistently included in the observatory’s routine work. In 1970, HVO switched to computer-based earthquake location procedures by applying the HYPOLAYR program (Eaton 1970) using P-wave arrival-times and a layer-cake velocity model. In 1979, HVO started the Eclipse computing configuration and the HYPOINVERSE earthquake location program (Klein 1978), which allows the use of depth-varying gradient velocity models and station corrections.

From 1986 to 2009, HVO was based on the Caltech-USGS Seismic Processing (CUSP) system (Dollar 1989; Lee et al. 1989) for real-time digital data acquisition and automated, near-real-time event detection and location. In early 2009, the monitoring system was changed to the the Advanced National Seismic System (ANSS) (US Geological Survey 1999) Quake Monitoring System (AQMS) (Renate Hartog et al. 2019). Regardless of the monitoring system, HYPOINVERSE has remained the main location program. Thelen (2014) reviewed the earthquake location methodologies used by HVO. During the unprecedented 2018 Kilauea eruption, 7 telemetered seismic stations (with 4 in the LERZ and 3 in the summit area) were lost, and 11 (with 9 in the LERZ and 2 in the summit) were added to the monitoring network. Shiro et al. (2020) presented the changes in HVO’s monitoring at Kilauea volcano before, during, and after the 2018 eruption. Figure 5 shows the distribution of HVO seismic stations in operation at the time of writing (June 2022). The majority of these stations were upgraded with sufficient bandwidth and dynamic range since 2010 (Okubo et al. 2014). The number of stations is consistent with the magmatic and seismic activity on the island,

with Kīlauea as the most densely monitored volcano, followed by Mauna Loa. Within Kīlauea, the areas around its summit and Pu‘u‘Ō‘ō are the most densely monitored.

HVO issues updates for the active volcanos of Hawai‘i as activity warrants. The daily seismicity rate is shown in Fig. 6a for all the detected events in HVO’s digital record from 1986 to 2018. About 20% of these events are not included in the final earthquake catalog (Fig. 6b), because there are not enough quality arrivals or resources to determine the location of every single event. In Fig. 7a–c, the HVO location distribution of earthquakes in 1997 is shown, when new fissures erupted in Kīlauea’s East Rift Zone (e.g., Owen et al. 2000; Lin et al. 2015). The eruption started on January 30, 1997 and lasted 22 hours, causing the abrupt increase in seismicity rate (Fig. 6). A couple of features are revealed in the HVO locations, one is the absolute earthquake depth (e.g., beneath the summit area) and the other is the relative location (e.g., in the south flank). In the summit area, the earthquake depths are all equal to or greater than 0 km, with the abrupt stop at 0 km depth. This is because in 1-D earthquake location, the inverted depth is often the average elevation of all the stations used in the location process. At HVO, before 2018, the reported depth of each earthquake was the average elevation of the five closest recording stations and the zero elevation was different for every earthquake (<https://www.usgs.gov/observatories/hvo>), which could introduce confusion when comparing depths of different earthquakes. This ambiguity manifests the significance of 3-D location, in which the reference zero depth is usually the mean sea level in the study area. Figure 7d–f shows the 3-D locations for the same number of earthquakes by Lin and Okubo (2016). The most significant difference between the HVO and the 3-D catalogs is in absolute location, observed in both the summit area and the south flank. Starting with these 3-D relocations, relative earthquake location accuracies were improved by using differential times from waveform cross-correlation (Fig. 7g–i). A dramatic sharpening of seismicity is obtained in the south flank (Fig. 7i), more clearly showing the linear sub-horizontal *décollement* between the volcanic edifice and oceanic crust. Similar wave-

form cross-correlation relocations by Matoza et al. (2020) are shown in Fig. 7j–l, starting with the HVO locations. Note that since 2018 and when this relocation study was conducted, HVO, along with other observatories and seismic networks that used AQMS, had corrected the systematic bias in earthquake depths caused by topography and the new zero-reference for all the events is mean sea level, same as in the 3-D relocations.

5.2 Alaska

Alaska and the adjacent Aleutian subduction zone are one of the most seismically active regions in the United States with very complex tectonic settings. The region has been seismically monitored by several regional networks, including the Alaska Volcano Observatory (AVO), the Alaska Earthquake Center, and the National Tsunami Warning Center (Fig. 8a). The latter two mainly monitor large earthquakes and tsunami hazards in Alaska, and AVO focuses on the smaller earthquakes near volcanoes. Because of the mission of AVO and the focus of this chapter, I only discuss the seismic monitoring by AVO. Nonetheless, it is worth noting that the seismic data used in this section are the joint efforts of all the above agencies. AVO was formed in 1988 and is a joint program of the U.S. Geological Survey, the Geophysical Institute of the University of Alaska Fairbanks, and the State of Alaska Division of Geological and Geophysical Surveys. According to AVO, there are over 130 volcanoes and volcanic fields that have been active since the last two millions years. About 90 of them have been active within the last 10,000 years (pink inverted triangles in Fig. 8b), 54 of which have been active within historical time (since about 1760, blue inverted triangles in Fig. 8b, Cameron and Schaefer 2016). On average, one or two Alaskan volcanoes erupt each year. Initially, AVO monitored the four volcanoes in Cook Inlet (Mount Spurr, Redoubt, Iliamna, and Augustine, Fig. 9) because of their proximity to Alaska population centers. Over the past three decades, AVO has established a seismic network of over 200 stations with 25 subnetworks and expanding coverage out to the western Aleutian

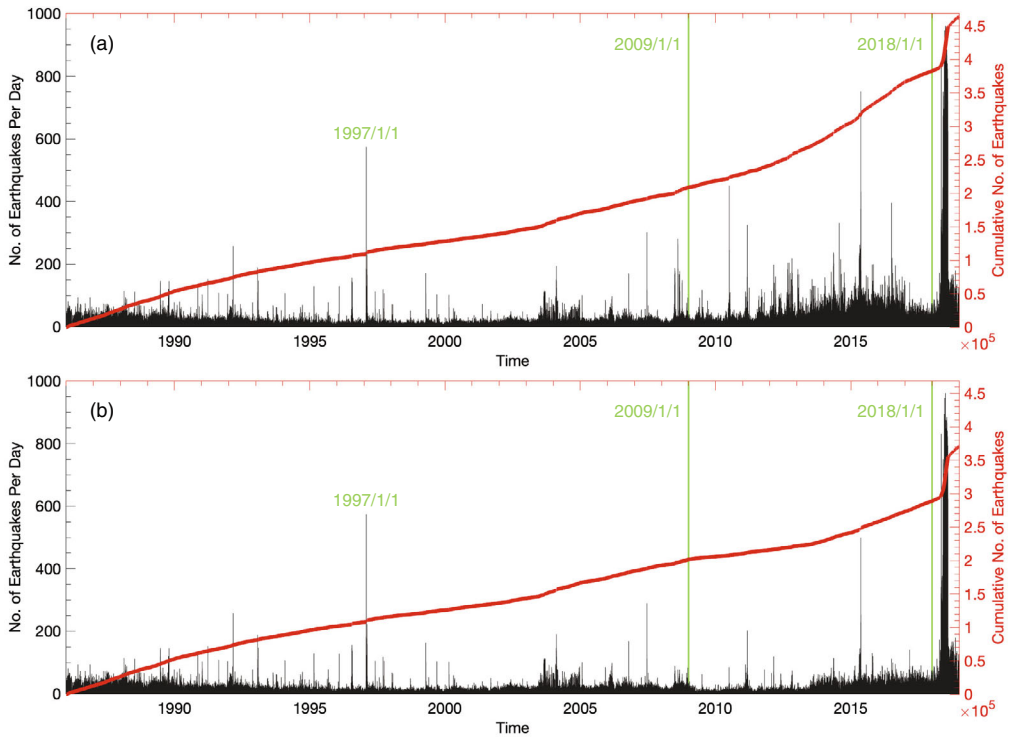


Fig. 6 Daily seismicity rate from January 1, 1986 to December 31, 2018 on the island of Hawai'i. **a** All the events detected by HVO; **b** All the events located by HVO. Red thick curves illustrate the cumulative number of earthquakes. The increase in January 1997 corresponds to the

fissure eruption in Kīlauea's East Rift Zone. In 2009, HVO made significant improvements to both its field seismographic stations and its seismic computing environment. The dramatic Kīlauea eruption commenced on May 3, 2018

Islands (Dixon et al. 2019). Since 2014, AVO has been seismically monitoring 34 volcanoes. Seismic data recorded by the stations are transmitted to AVO central offices with either analog or digital telemetry.

Similar to HVO, there have been numerous changes and upgrades of the monitoring systems at AVO, mainly due to the development of technology, computer, and computer programming. Before February 2002, data were recorded on the IASPEI system (Lee et al. 1988) and the main processing programs were the event-detecting algorithm XDETECT (Rogers 1993), the waveform-picking program Xpick (Robinson 1990) and hypocenter-locating program Hypoellipse (Lahr 1999). Classification codes are provided based on visual inspection for VT earthquakes, LP events, explosion events, regional tectonic earthquakes, teleseismic events, or non-seismic events (Dixon et al. 2002). In

March 2002, data recording and event detection were switched to the open-source system Earthworm (Johnson et al. 1995). Dixon et al. (2005) conducted a detailed comparison of event detection between IASPEI and Earthworm acquisition systems for Alaskan volcanoes and showed the Earthworm system to be more effective at detecting events in volcanic settings using the relatively sparse seismic networks. In February 2012, data acquisition for the AVO seismic network was transitioned to the ANSS Quake Monitoring System–AQMS (Renate Hartog et al. 2019) and Hypoinverse for location (Klein 1978, 2014). The location process is conducted based on a regional 1-D velocity model combined with local cylindrical models for each of the monitored volcanoes. AVO is currently working on automatically incorporating cross-correlation detections and relocations (Tan et al. 2021). USGS provides yearly summary documents of

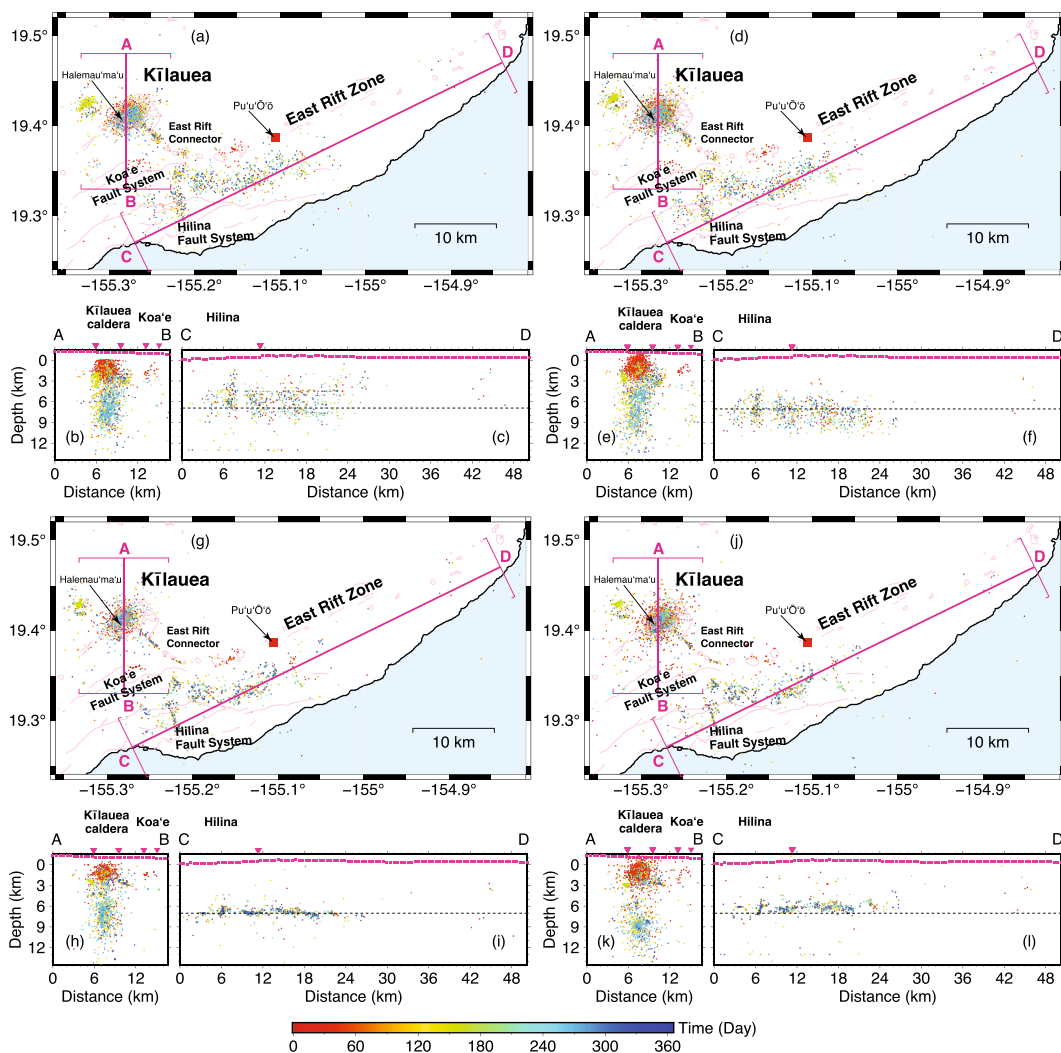


Fig. 7 Distribution of the 5,100 earthquakes in 1997 in Kilauea volcano. Events are colored by days in the year. Note that only common earthquakes from all the catalogs are plotted. **a–c** Initial HVO locations; **d–f** 3-D relocations from Lin and Okubo (2016); **g–i** Waveform cross-correlation relocations from Lin and Okubo (2016); and **j–l** Waveform cross-correlation relocations by Matoza et al. (2020). **a, d, g, j** Map view. The pink straight lines A-B and C-D represent the depth profiles for the cross-section views. Small bar at the end of each profile shows the width for the seismicity projection. **b, e, h, k** Depth distributions

along profile A-B. **c, f, i, l** Depth distributions along profile C-D. The pink dotted curve at the top of each cross section illustrates local ground surface before the 2018 activity. Zero depth corresponds to mean sea level (~ 1.1 km below ground surface near summit caldera and 455 m below ground surface in the eastern south flank). Inverted triangles mark the locations of some major geological structures, including Kilauea summit caldera and the Koa'e and Hilina fault systems. The horizontal dotted line denotes 7 km depth below mean sea level, where the décollement is located

AVO network/subnetwork status and highlights of seismicity at Alaska volcanoes (e.g., Dixon et al. 2019; Power et al. 2019).

In Fig. 9, distributions of earthquake locations in 2016 are shown from different catalogs for

south Alaska. In 2016, AVO located 6,151 earthquakes in its monitored area (Dixon et al. 2019). Figure 9a–b shows the distribution of these earthquakes near AVO's first four monitored volcanoes (Mount Spurr, Redoubt, Iliamna, and

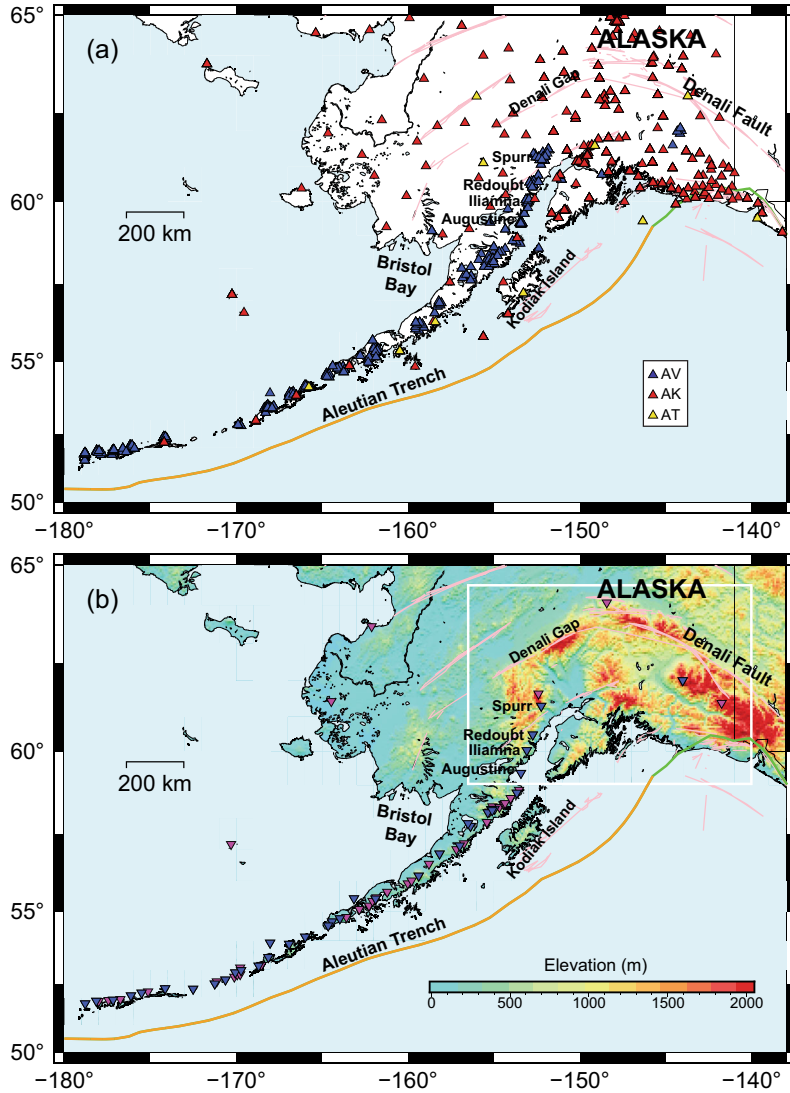


Fig. 8 Distributions of the regional seismic stations (a) and volcanoes (b) in Alaska and the Aleutian subduction zone. Abbreviations for the three seismic networks in (a) are AV, Alaska Volcano Observatory; AK, Alaska Earthquake Center; and AT, National Tsunami Warning Center.

Pink inverted triangles in (b) represent the Holocene volcanoes and blue ones for those within historical time (since about 1760). The white box shows the location of the study area in Fig. 9. Other symbols are the same as those in Fig. 5

Augustine). The majority of these earthquakes are shallow (above 15 km depth below sea level) and small (magnitude < 2) within 20 km of an AVO-monitored volcano. Seismic data for 2016 earthquakes are also downloaded from the USGS website (<https://earthquake.usgs.gov/earthquakes/search/>), shown in Fig. 9c–d. These data are the joint efforts of multiple agencies, including Alaska Volcano Observatory, Alaska

Earthquake Center, and the US Transportable Array. For completeness, deeper events are also included. Note that though the AVO velocity models extend to 65 km below sea level or shallower, AVO does provide earthquake information and phase arrivals for deeper events. Recently, a large-scale waveform cross-correlation relocation was applied to the Eastern Aleutian-Alaska Subduction Zone (Fig. 9e–f, Aziz Zanjani and

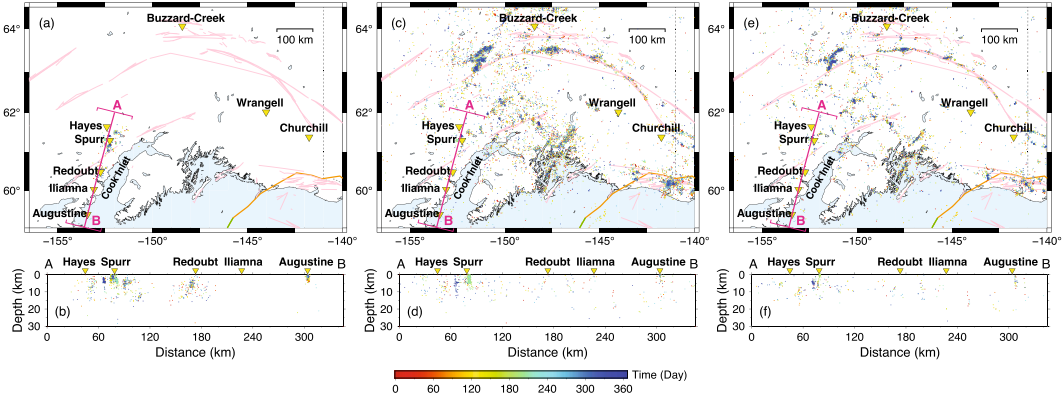


Fig. 9 Distribution of the earthquakes in 2016 in south Alaska, where the first four AVO-monitored volcanoes (Mount Spurr, Redoubt, Iliamna, and Augustine) are located. Events are colored by days in the year. **a–b** AVO located earthquakes; **c–d** Earthquake locations downloaded from USGS; and **e–f** Waveform cross-correlation relocations by Aziz Zanjani and Lin (2022). Note that only

common earthquakes from the USGS and the waveform cross-correlation catalogs are plotted in (**c–f**). **a, c, e** Map view. Pink straight lines are the profiles for the cross sections. Small bars at the end of the profile show the width for the seismicity projection. **b, d, f** Depth distributions of seismicity within ± 50 km distance across profile A-B. The vertical exaggeration is 2

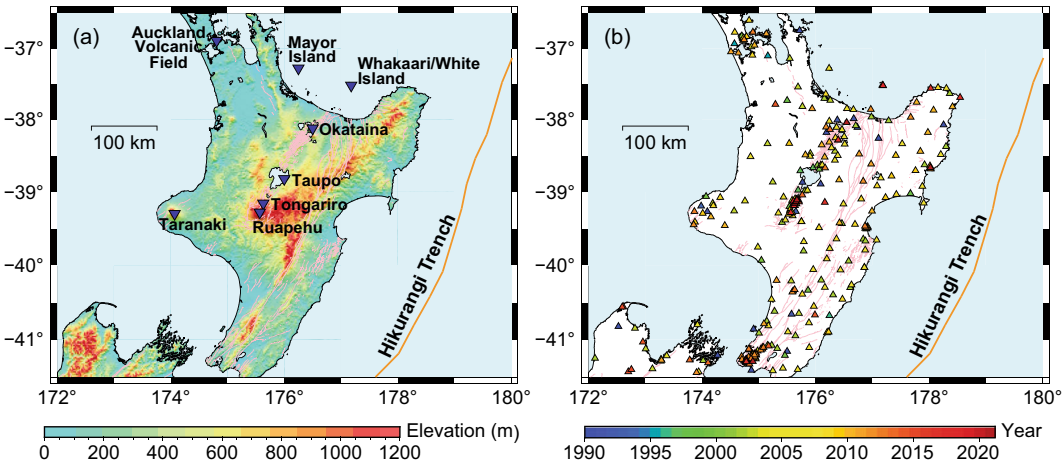


Fig. 10 Distributions of the Holocene volcanoes (inverted triangles in (**a**)) and GeoNet seismic stations (triangles in (**b**)) on the north island of New Zealand near the Hikurangi

subduction zone. Symbols are the same as those in Fig. 5. Fault lines are obtained from Langridge et al. (2016)

Lin 2022). They improved absolute earthquake location accuracies by taking advantage of an available 3-D seismic velocity model (Nayak and Thurber 2020) and the tele-tomoDD algorithm (Pesicek et al. 2014, and then applied a differential-time relocation method based on waveform cross-correlation (Lin 2018) to improve relative location accuracies. Although the focus of their study was on intermediate-depth seismicity, the results show significant

improvements in location accuracies of shallow earthquakes as well, compared to the initial catalog.

5.3 New Zealand

The North Island of New Zealand manifests distinct volcanic features in its northern and southern portions (Fig. 10a), with Calc-alkaline volcanoes and back-arc basins in the north, includ-

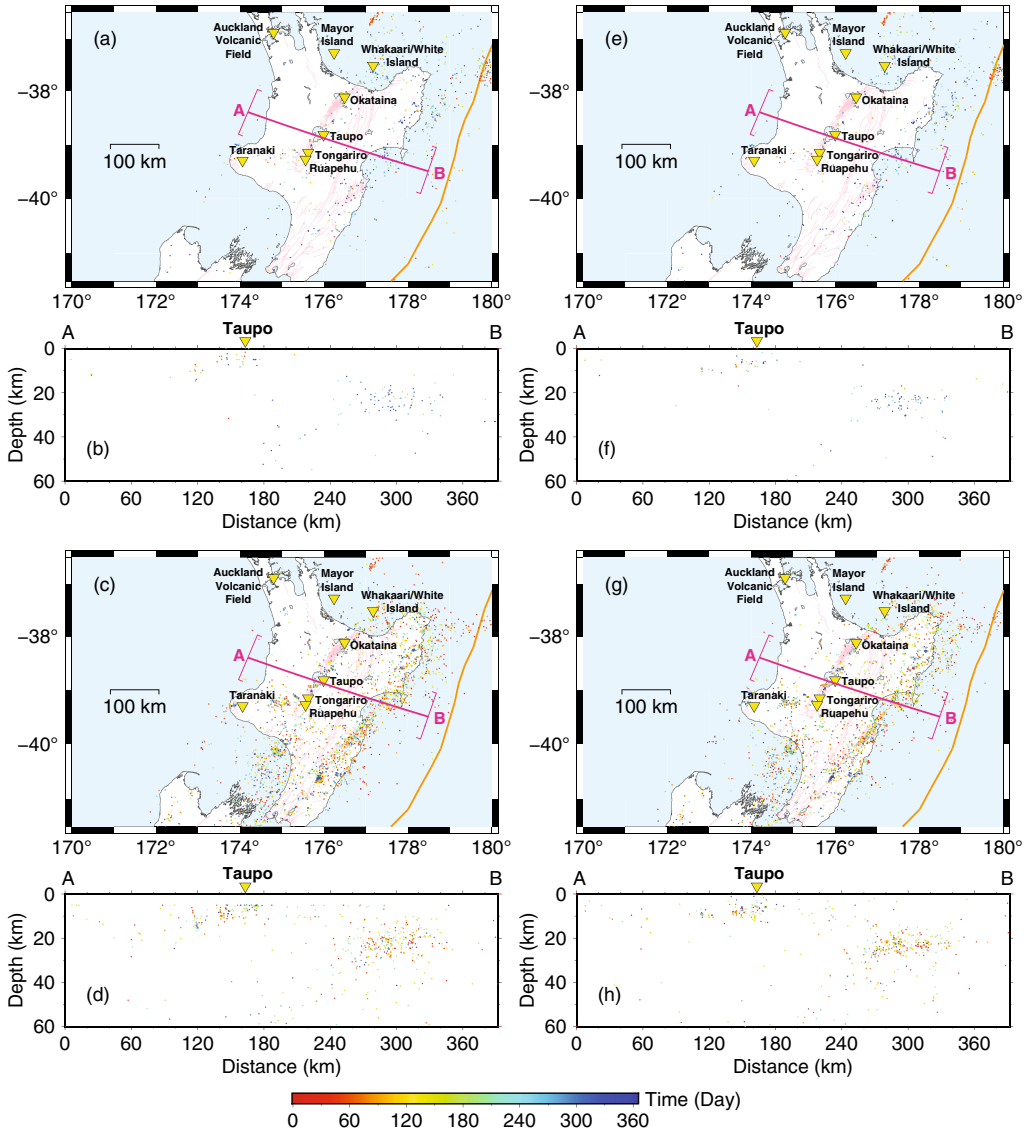


Fig. 11 Distribution of the earthquakes in 2015 on the north island of New Zealand. Events are colored by days in the year. **a, b** GeoNet 1-D locations; **c, d** GeoNet 3-D locations; **e, f** Waveform cross-correlation relocation starting with the GeoNet 1-D locations (Aziz Zanjani et al. 2021);

and **g, h** Waveform cross-correlation relocations starting with the GeoNet 3-D locations (Aziz Zanjani et al. 2021). **a, c, e, g** Map view. Pink straight lines are the profiles for the cross sections. **b, d, f, h** Depth distributions along profile A-B. The vertical exaggeration is 2

ing the Taupo Volcanic Zone (TVZ), whereas no volcanic activity in the south. The TVZ is highly active, consisting of volcanoes with eruption histories over the past two million years (Wilson et al. 1995), and shows distinguishable volcanic activity from north to south. The volcanoes at its northern and southern ends are predominantly andesitic composite cones with no calderas, whereas those

in the central section are typically rhyolitic with large calderas (Fig. 10a, Wilson et al. 1995). Andesitic volcanism also occurs at Mt Taranaki, about 130 km west of Mt Ruapehu volcano at the southern end of the TVZ.

Even though New Zealand had been long monitored with seismic instruments since 1884, earthquake location studies did not start until

1930s. In 1964, modernization began at GeoNet (Fig. 10b, <https://www.geonet.org.nz/>) with earthquakes located by computers and reviewed by seismologists. Earthquakes between 1942 and 1986 were reprocessed by applying the LOCAL and MICRO software packages (Smith 1979). A revised CUSP system (Dollar 1989; Lee et al. 1989) was the main processing system from 1987 to 2011. Since 2012, SeisComp3 (Helmholtz Centre Potsdam 2008; Olivieri and Clinton 2012) has been the analysis system at GeoNet, featured with two location techniques, LocSAT (Bratt and Nagy 1991) using the 1-D model of iasp91 (Kennett and Engdahl 1991) and NonLinLoc that adopts the 3-D seismic velocity model for New Zealand by Eberhart-Phillips et al. (2010). In Fig. 11, distributions of the earthquakes in 2015 are shown for the north island of New Zealand. Only a small percentage of these events are located by the 1-D velocity model (Fig. 11a–b) and the majority of the GeoNet locations are the 3-D locations (Fig. 11c–d). Waveform cross-correlation relocation by Aziz Zanjani et al. (2021) starting with these locations are shown for comparison (Fig. 11e–h). The cross-correlation approach improves the relative locations of earthquakes, resulting in clustering and clearer features in the distribution of events.

6 Conclusions

Volcanic eruptions are one of the most hazardous natural disasters on Earth. In order to improve our understanding of eruption processes and volcano-earthquake interactions to reduce life and property loss, we need improved data quality and more robust estimation methods to monitor and study volcanic systems. The three case studies, Hawai'i, Alaska, and New Zealand, are among the most seismically active and best monitored volcanic regions. High-precision earthquake relocations are essential for mapping magma migration and are useful for future real-time analysis of seismic data in volcanic systems and for investigating the history and current states of volcanoes and calderas. Waveform cross-correlation has proven

to be a valuable tool for assessing fine-scale volcanic structures, but has not been routinely applied to volcanic areas.

Acknowledgements I thank the U.S. Geological Survey, the Hawaiian Volcano Observatory, Alaska Volcano Observatory, and the New Zealand GeoNet project for providing data used in this study. I am grateful to the Editors and the two Reviewers for the constructive suggestions. Plots were made using the public domain GMT software (Wessel et al. 2013) and Matlab. Funding for this research was provided by the National Science Foundation grant EAR-1928158.

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Monitoring LP and VLP Seismicity

Jürgen Neuberg, Dinko Sindija, and Rodrigo Contreras-Arratia

Abstract

Long-period (LP) and very-long-period (VLP) volcanic events are distinct seismic signals and very different in frequency, waveform and source character from any other earthquake-related tectonic event. While LPs play an important role as a potential forecasting tool, VLPs fill the gap between the classic seismic frequency band and monitoring of ground deformation. VLP signals have been recorded on volcanoes in the last three decades only due to the increased availability of broadband seismic sensors in monitoring networks. We describe the distinct characteristics of LPs and VLPs in order to identify both and provide source models, which are necessary for their interpretation in terms of the underlying volcanic processes. When we describe several procedures and processing steps to extract all

the information these important signals contain we focus on applications in an operational monitoring environment rather than on theory. These procedures range from testing seismic moment tensor inversions for sufficiently dense networks to minimal approaches with only a few seismic sensors. We conclude this chapter with a check list for monitoring staff which provides advice regarding the design and deployment of seismic networks as well as the necessary processing steps to extract maximum information.

1 Introduction to LPs and VLPs

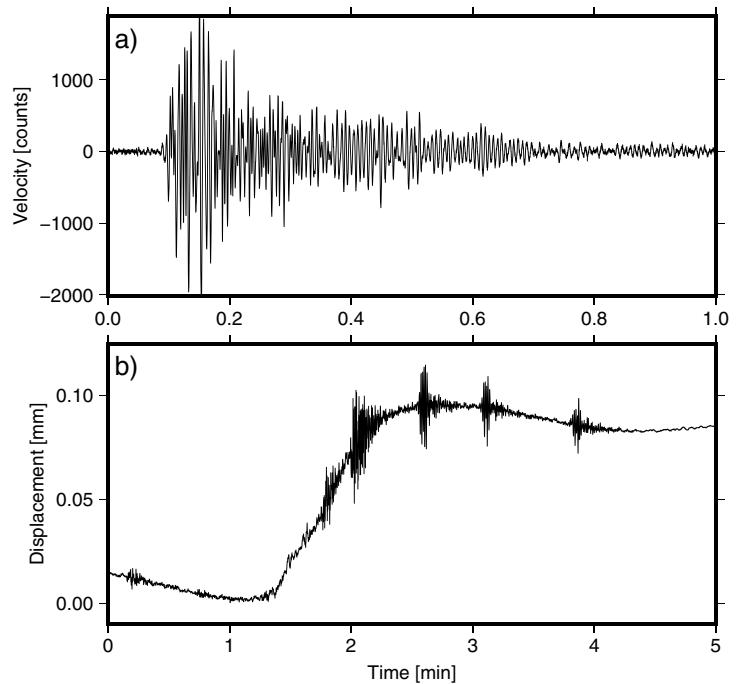
Long-period seismic events are an important class in the spectrum of volcanic seismicity as their occurrence alone has been used in the past as an indication for an imminent volcanic eruption (Cruz and Chouet 1997), even though their source and trigger mechanism had not been conclusively explained. They occur in all volcanic environments including hydrothermal systems and are often associated with magmatic fluids. LPs occur in the frequency band between 0.5 and 5 Hz and can be easily detected with a short-period seismometer, leading to an apparent paradox in nomenclature. The frequency content can vary widely from one volcano to another, and even one single LP event can be recorded at the

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Fig. 1 **a** Example of a LP signal observed at station RETU, Tungurahua volcano, Ecuador on January 31st, 2014, and **b** VLP event recorded at station MBWW, Soufrière Hills volcano, Montserrat, on March 23rd, 2012. Note that the VLP has undergone several processing steps described below to extract the shown step-like waveform, superimposed are several high-frequency VT events



same volcano with an additional high-frequency component that can differ from one seismic station to another. This led to the term ‘hybrid event’, sometimes also referred to as ‘low-frequency event’ when grouped together with LPs (Neuberg et al. 2000). Due to their emergent onset and the lack of a clear *S* wave arrival it is often difficult to find reliable source locations for small amplitude events. They exhibit amplitude spectra with several dominant spectral peaks suggesting some kind of resonance behaviour.

In contrast, very-long-period signals are associated in a volcanic environment with the movement of magma or volatiles typically in the time frame of tens to hundreds of seconds. This transient behaviour places VLPs in the gap between classic seismology and ground deformation. Two waveform examples are depicted in Fig. 1.

Several key references describe the role LPs and VLPs play in the variety of volcano-seismic signals, e.g. Chouet and Matoza (2013), and shorter summaries are presented by McNutt (1996) and Neuberg (2021). While these references cover different volcanic and hydrothermal settings, we will focus in this chapter on the specific relevance of LPs and VLPs in silicic volcanic

environments where we explore potential links between volcano monitoring, geophysical models and forecasting volcanic behaviour.

1.1 Specific Relevance of LPs

LPs have been detected as single individual events but more often they occur in seismic swarms of repetitive signals with similar waveforms. Furthermore, these swarms show an accelerating behaviour in occurrence and sometimes in amplitude at the same time which can be linked to an acceleration in magma ascent. The fact that LP swarms often—but not always (Arambula-Mandoza et al. 2018)—preceded a dome collapse on several volcanoes raised some hope to use seismicity rates as a proxy for magma ascent rates, with the aim to detect a critical threshold in ascent rate that is followed by a dome collapse. In this context, we discuss two approaches that attempt to exploit these LP characteristics further.

An empirical approach compared the accelerating character of LP swarms with accelerating micro seismicity preceding landslides, or in more general terms, with the material failure law

(Voight 1998; Hammer and Neuberg 2009; Salvage and Neuberg 2016). This method leads to a simple but very useful tool, that can be easily implemented into data monitoring streams where earthquake rates are plotted versus time, and their inverse value tends towards zero when the acceleration increases as a power law. This technique will be further discussed below. An alternative, more physics-based approach aims at the understanding of the actual source process or trigger mechanism of LPs that are generated in the volcanic conduit (Neuberg et al. 2006; Iverson et al. 2006), as well as the interpretation of the low-frequency content and its fluctuations in terms of magma properties (Neuberg and O’Gorman 2002; Thomas and Neuberg 2012).

1.2 Specific Relevance of VLPs

In contrast, VLPs have dominant periods between tens to several hundreds of seconds. When the periods of these signals fall into the far end of the range they are often referred to as ultra-long period (ULP) seismic signals, e.g. Fontaine et al. (2019); however, a clear period threshold has not been defined yet. VLPs can only be detected if at least a few broadband seismometers with eigenperiods of at least 30 s are part of the monitoring network, and even if such instruments are in use, certain processing steps are necessary to identify VLPs in the daily monitoring routine. If genuine, i.e., not generated by an instrument effect, these signals are indicative of mass movements of magmatic fluids such as gas or melt in the volcanic edifice, or changes to the geometry of the volcanic plumbing system. To link the VLP seismogram to volcanic source mechanisms further processing steps are necessary to retrieve the true ground motion at the recording site.

2 Source Models for LPs

The key to understand LP signals lies in contrasting them to normal, tectonic earthquakes which are caused by a sudden stress release along a part of a fault from which seismic waves

propagate in all directions through the adjacent medium to a recording site. In contrast, the seismic energy released by a LP is trapped at the boundary between a fluid embedded in a solid in the form of a ‘crack wave’ or ‘tube wave’. For a vertical fluid-solid boundary the solutions to the wave equations for horizontal and vertical displacement are, e.g. Ferrazzini and Aki (1987)

$$u_x = (-\Phi \ell_p e^{-\ell_p x} - i k_z \Psi e^{-\ell_s x}) e^{i(k_z z - \omega t)} \quad (1)$$

$$u_z = (-i \Phi k_z e^{-\ell_p x} - \Psi \ell_s e^{-\ell_s x}) e^{i(k_z z - \omega t)} \quad (2)$$

where Φ and Ψ are P and S wave potentials, and $\ell_p = \sqrt{k_x^2 - \frac{\omega^2}{\alpha^2}}$ and $\ell_s = \sqrt{k_x^2 - \frac{\omega^2}{\beta^2}}$ with α and β the P and S wave velocity, ω the angular frequency, and k_x and k_z the horizontal and vertical wave number, respectively. Without going into detail one can see from Eqs. (1) and (2) that the amplitude term in brackets decreases with increasing distance $e^{-\ell x}$ away from the vertical boundaries, and the phase term $e^{i(k_z z - \omega t)}$ indicates a wave propagation in vertical direction only. This results in a vertically propagating, trapped wave that might interact with the free surface if the fluid (conduit, crack or dyke) reaches the surface, and a reflection at depth where the extent of the fluid body is limited or merges with another body with different seismic properties. The slow phase velocity of this wave (Ferrazzini and Aki 1987) explains the long-period character of the LP while the fact that the wave is trapped supports the concept of a resonance.

2.1 Resonance of Dykes, Sills and Conduits

The resonance behaviour of the tube or crack wave discussed above is governed by the so-called stiffness factor that was introduced by Aki et al. (1977) as $C = \frac{bL}{\mu w}$ where b is the bulk modulus of the fluid, L and w are the length and thickness of the fluid body, respectively, and μ is the rigidity of the embedding, elastic solid. What is here described as the ‘fluid body’ embedded in a solid can be a crack, a dyke or a conduit in

volcanic settings, or indeed any thin, soft layer with high impedance contrast with regards to the embedding, elastic solid. Hence, a fault gouge has been suggested to explain the occurrence of LP seismicity in subduction zones (Kikuchi and Fukao 1987) while Chouet (1996), among others, modelled several resonance modes of cracks and determined the corresponding dimensions and physical parameters.

The definition of the stiffness factor also reveals the trade-off between the controlling parameters: an increase in bulk modulus, e.g. by the loss of volatiles in the magma, can be compensated by either a similar increase of rigidity in the solid medium or by widening of the conduit over time and would lead to the same resonance behaviour. This is why different studies on LP seismicity on volcanoes suggest very different source parameters for the same observed low frequency: an ash laden crack with a width of a few centimetres, e.g. Molina et al. (2004) competes with a dyke filled with bubbly magma, e.g. Neuberg et al. (2000) as a source mechanism for LP resonance. The only way to break this trade-off is to fix some of the parameters by taking geological/petrological data into account and offer in general a wider range of interpretations, e.g., the estimation of the quality factor of LP events can give some indication on the type of magmatic fluid (Kumagai and Chouet 2000).

2.2 Trigger Mechanisms of LPs

Several trigger mechanisms have been proposed to set off a low-frequency resonance in a magmatic system. These include magma-water interaction (Zimanowski 1998; Matoza and Chouet 2010), magma flow instabilities (Julian 1994), stick-slip motion of magma plugs (Goto 1999; Iverson et al. 2006), periodic release of gas-ash mixtures into open cracks (Molina et al. 2004), slowly ascending plugs of highly crystallized magma without any fluid component (Bean et al. 2014), and repeated, brittle fracturing of magma in glass-transition under high stress conditions (Neuberg et al. 2006). If we focus on volcanic systems with high viscosity magmas, the characteristics of low frequency

seismicity can be summarized as: (i) they often occur in seismic swarms, (ii) some events can be grouped in ‘families’ of similar waveforms, (iii) the occurrence is highly regular leading to characteristic lines in spectrograms, (iv) with increasing occurrence the events often merge into continuous tremor. Most importantly, (v) major dome collapses or accelerated magma ascent are preceded by low-frequency seismicity, however, the occurrence of low-frequency seismicity is not always followed by a dome collapse. Most of these characteristics can be seismologically interpreted as a stationary seismic source with a repetitive, non-destructive source mechanism.

Another important observation has been made on Tungurahua volcano in Ecuador (Marsden et al. 2019) and on Soufrière Hills volcano, Montserrat (Green et al. 2006): low-frequency seismicity is anti-correlated with the near-field deformation pattern as observed by tilt meters. When these observations and characteristics are combined with three-dimensional modelling of magma flow in a conduit a picture emerges that can reconcile all aspects in one single model that is close to the idea of brittle failure of magma in glass transition. This model is not *necessarily* the only explanation of low-frequency seismicity on volcanoes, as a resonance in a hydrothermal system, for instance, would produce a LP signal, although with different characteristics. However, if fluid flow of a viscous magma occurs in a conduit, then low-frequency seismicity will be generated if a critical shear stress is reached, hence this model offers a *sufficient* explanation for the generation of low frequency seismicity on volcanoes with high viscosity magmas.

The condition for such a trigger mechanism requires a critical vertical shear stress σ_c within the conduit with radius r , such that brittle failure can occur, hence

$$\sigma = \mu \frac{\partial}{\partial t} \frac{\partial z}{\partial r}, \quad (3)$$

the product between vertical strain rate and shear viscosity μ must reach a critical value. The strain rate can be expressed through the vertical magma ascent velocity $V_z = \partial z / \partial t$ and brittle failure occurs if

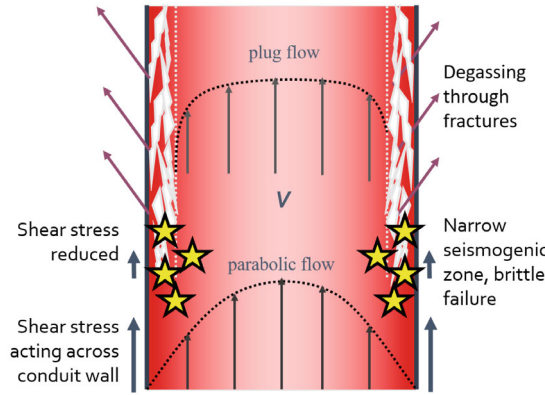


Fig. 2 Conceptual model for LP trigger, tilt generation through shear stress and shear stress partitioning adapted from Neuberg et al. (2006). Strain rate and viscosity reach a critical value such that the resulting shear stress is higher

than yield strength of magma leading to brittle failure and LP generation. Shear stress that causes traction across the conduit wall and deformation at lower level is reduced due to LP generation

$$\sigma = \mu \frac{\partial V_z}{\partial r} \geq \sigma_c. \quad (4)$$

This condition is satisfied near the conduit wall where the velocity gradient $\partial V_z / \partial r$ is increased when plug flow replaces Poiseuille flow and cooling leads to a high viscosity μ such that the critical shear stress $\sigma_c \approx 10$ MPa can be reached (Neuberg et al. 2006; Thomas and Neuberg 2012) (Fig. 2).

The ascending, viscous magma also exerts a shear stress across the conduit wall which explains the deformation in the near-field of the conduit, as well as its anti-correlation with seismicity. When the shear stress across the conduit wall is reduced by the generation of shear failure within the conduit setting off seismicity, the deformation (tilt) signal goes through an inflection point and decreases (Green et al. 2006). These relationships are important for the understanding of magma flow dynamics and their role in estimating magma ascent rates through seismic observations which we attempt in the following sections.

2.3 Link to Harmonic Tremor

In the previous section we mentioned the occurrence of LPs in swarms with similar waveforms, hence caused by a repetitive triggering within a limited source region. Sometimes such a trigger

mechanism acts in a very regular manner such that the trigger can be described by a ‘comb-function’, a time series comprising a series of delta functions separated by constant spacing in time. If we consider each delta function as a trigger in time then the resulting LP can be represented by a convolution of trigger and a wavelet that describes each brittle failure process of magma along the conduit wall as described above and depicted in Fig. 2. The source characteristic of that failure is captured in the frequency contents of the wavelet.

If we describe the single wavelet as $f(t)$ and its Fourier spectrum as $F(\omega)$ with angular frequency ω , and the series of triggers, the ‘comb-function’, as $c(t)$ with its Fourier spectrum $C(\omega)$ then the resulting seismic trace will be given by $s(t) = c(t) * f(t)$, where $*$ denotes convolution, and the corresponding spectrum will be the product $S(\omega) = C(\omega) F(\omega)$. In case $c(t)$ provides a very regular comb-function, its Fourier spectrum $C(\omega)$ is again a comb-function, hence will produce a regular pattern of horizontal lines in a spectrogram. These lines covering the entire frequency range and are separated by $\Delta\omega = 2\pi/\Delta t$ where Δt is the spacing of triggers in time.

We include this aspect here as it has a very practical application. Often LP swarms, where single events are still separable, merge into what is often referred to as ‘harmonic tremor’ where single events cannot be any longer separated. How-

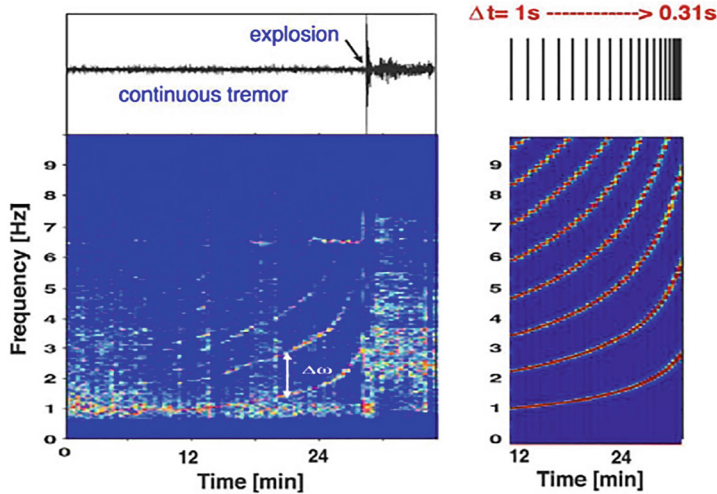


Fig. 3 Spectrogram of a tremor episode of Soufrière Hills volcano on January 7, 1999. The distance between the spectral lines $\Delta\omega$ increases as the spacing in time Δt decreases representing an acceleration of swarm activity of LPs. The right panel shows the synthetic comb-function accelerating

the trigger Δt from 1 to 0.3 s. Note that the spectrogram shows only the lines in a frequency range determined by the bandwidth of the wavelet $f(t)$ restricted by the convolution

ever, if the occurrence of merged events is regular enough a spectrogram will display horizontal lines in the frequency range of the single wavelet, and one can still derive the trigger rate Δt , and its temporal behaviour $\partial\Delta t/\partial t$ by determining $\Delta\omega$. This can have important implications when we link the acceleration of the seismic trigger rate with the critical ascent rate of magma (Fig. 3).

ity reported by MVO, and in particular a family of events (family A) investigated by Green and Neuberg (2005) and the corresponding cumulative seismic moment (Fig. 4).

3.1 Accelerated Ascent Rate and the Material Failure Law

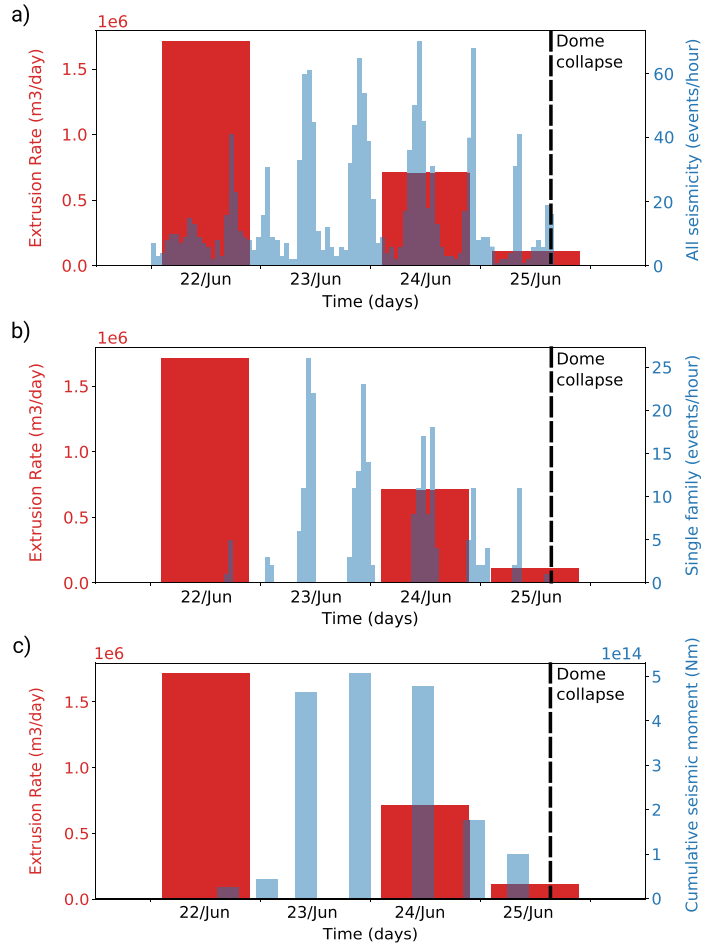
3 LPs as Forecasting Tool

As previously mentioned, LP events have been used as a forecasting tool on several volcanoes. In an accelerating system, the increased magma ascent rate and temperature within the magma body produce a plug-like fluid ascent with large velocity gradients experienced by the magma in glass transition. As shown in the previous section, these gradients produce high shear stresses triggering LP events (Fig. 2). A critically high LP rate of occurrence has been linked to dome collapse events through the material failure law (Voight 1998; Hammer and Neuberg 2009).

The case study for this chapter is taken from the eruption of Soufrière Hills volcano in Montserrat where we focus on the time period between June 22–25, 1997. We re-analyse the seismic-

Based on the source models for LPs previously mentioned, the combination of viscous magma and high strain rates produce shear stresses that can overcome the yield strength of magma and produce brittle failure at the conduit wall (Denlinger and Hoblitt 1999; Neuberg et al. 2006; Thomas and Neuberg 2012, 2014). Theoretical studies (Denlinger and Hoblitt 1999) and data analysis (Voight et al. 1999; Green and Neuberg 2006; Neuberg et al. 2006) have shown that this behaviour is cyclic with periods of 8–10 h. De Angelis and Henton (2011) have studied the seismicity occurring between June 22 and 25, 1997, and estimated the dynamic values for magma ascent to analyse the feasibility of magma rupture for different viscosity values. Moreover, models of brittle magma failure (Hammer and Neuberg 2009; Salvage and Neuberg 2016) have been developed to forecast the time of dome

Fig. 4 Daily extrusion rates (red) and seismicity (blue) observed on Montserrat in June 1997. Extrusion rate and all seismicity (a), extrusion rate and seismicity of family A (b), and extrusion rate and cumulative seismic moment per swarm of family A (c) (Wadge et al. 2014; Green and Neuberg 2006)



collapse events, based on the rate of seismicity reaching a certain critical value.

The characteristics of the LP swarms observed prior to the dome collapse on June 25 1997, varies with time. In general, an acceleration is observed (Fig. 5), i.e. the number of events increase with time while event amplitudes do not change significantly over several swarms (Hammer and Neuberg 2009). Considering the inverse of the event rate as a function of time, we observe a decreasing linear trend of these values. The linear regression estimate intersects the time axis at the time a dome collapse is expected. Hammer and Neuberg (2009) calculated the seismicity rate every 10 min and averaged the data over the entire duration of each swarm; their results are shown in Fig. 5. Note that for later swarms the event rate is steeper and the peaks are narrower than for ear-

lier swarms where seismicity is distributed over a wider period. Hence, the accelerated seismic activity for a single family as depicted in Fig. 5 is fully captured by the shorter sampling interval of 10 minutes in comparison to Fig. 4 where all seismicity is displayed or averaged over an entire day.

This methodology, here (and most often) applied in hindsight, could provide a simple empirical framework for observatories to forecast the time window a dome collapse can be expected, merely based on the seismicity observed. The above example also demonstrates how the forecast window evolves by adding more data to the analysis. Furthermore, Salvage and Neuberg (2016) demonstrated that it is essential to apply this method to one single family of similar LP waveforms rather than using all seismic events, or even using RSAM data. Hence it is necessary

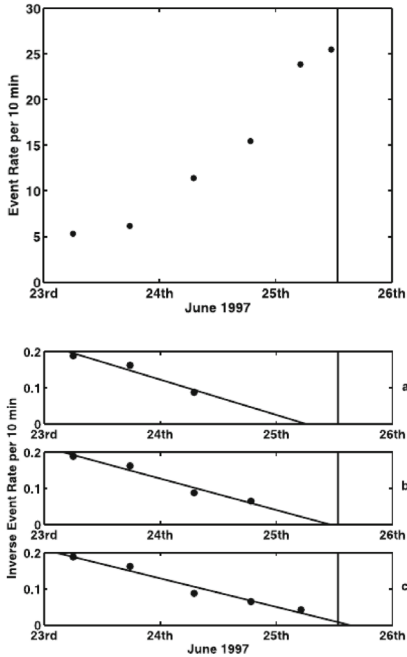


Fig. 5 Top: Averaged seismicity rates for 6 consecutive LP swarms. Bottom: **a** Inverse of the seismicity rate after three swarms, **b** after four swarms, and **c** after five swarms. The estimation of the timing for the dome collapse improves over time

to first identify and sort LP events into families by using a cross-correlation method where the full LP waveform is used to quantify waveform similarity. Green and Neuberg (2006) used a correlation threshold of 0.75 to define similarity within one family. This explains why the FFM method sometimes fails and why prior knowledge of event families is necessary for this type of analysis to succeed. Source migration or a change in source mechanism will result in evolving waveforms, hence, similarity will decrease until the correlation criterion for this particular event family is no longer met. However, this acceleration is not always observed making the method in those cases ineffective. A detailed discussion on the limitations of FFM can be found in Boué et al. (2016).

3.2 Curved Fault Geometries

The model for brittle failure of magma in the glass transition zone implicitly imposes a rupture

geometry that can be associated with these events. As magma ascends through a conduit in shallow depth, a planar rupture zone is not consistent with the geometry of the plumbing system comprising conduits and dykes. Alternatively, we propose curved rupture planes (Fig. 6), which do not adhere to linearity between seismic moment and entire area of rupture, valid for planar sources. This means that for identical rupture areas with different, e.g. curved, non-planar shapes, the seismic moments and magnitudes will be significantly different and need to be evaluated in a different way.

By using a superposition of single double couple sources Contreras-Arratia Neuberg (2019) have shown that for several complex non-planar sources (Fig. 6 left column) the amplitudes, magnitudes, waveforms and moment tensor solutions differ from the simple planar case. In particular, the full-ring rupture modelled as the summation of several pure-shear sources, provides a moment tensor that cannot be explained by the double couple source commonly used in seismology for this kind of source process. Furthermore, the seismic moment obtained is around 40 times smaller than that produces by the same-size planar rupture due to interference of adjacent rupture elements. Hence, the magnitudes are usually underestimated (Fig. 7). Furthermore, due to the geometry and interference of rupture elements located in pairs on opposite sites, the resulting waveform looks like the time derivative of the original time history. Hence, when interpreting the slip history on the fault in terms of a source process, e.g., a pulse in magma ascent, the signal after interference could be misinterpreted as magma ascent followed immediately by magma descent (see waveforms in Fig. 6c, g).

We use again data from the single family of low-frequency events occurred between June 22 and 25, 1997 (Green and Neuberg 2005), when the activity culminated in a dome collapse at 16:45 UTC. The intense cyclic occurrence is closely related to the magma extrusion observed during those days. We assume that the rupture occurs at the conduit wall simultaneously along a full-ring shape. By representing the seismic source as the superposition of individual sources, each section

Fig. 6 Rupture mechanisms, P-wave radiation patterns (S indicates South, normalised amplitude scale), displacement waveforms, polarisations at surface, and apparent moment tensors and magnitudes for different volcano-related sources. **a** Double couple (DC), **b** Compensated Linear Vector Dipole (CLVD), **c** Dyke aperture, **d** 1/4-ring rupture, **e** 1/2-ring rupture, **f** 3/4-ring rupture, **g** Full-ring rupture

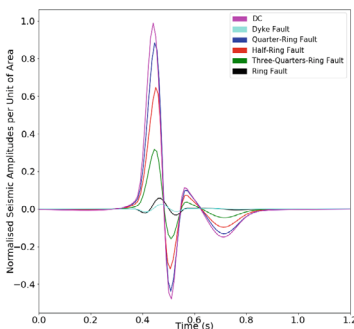
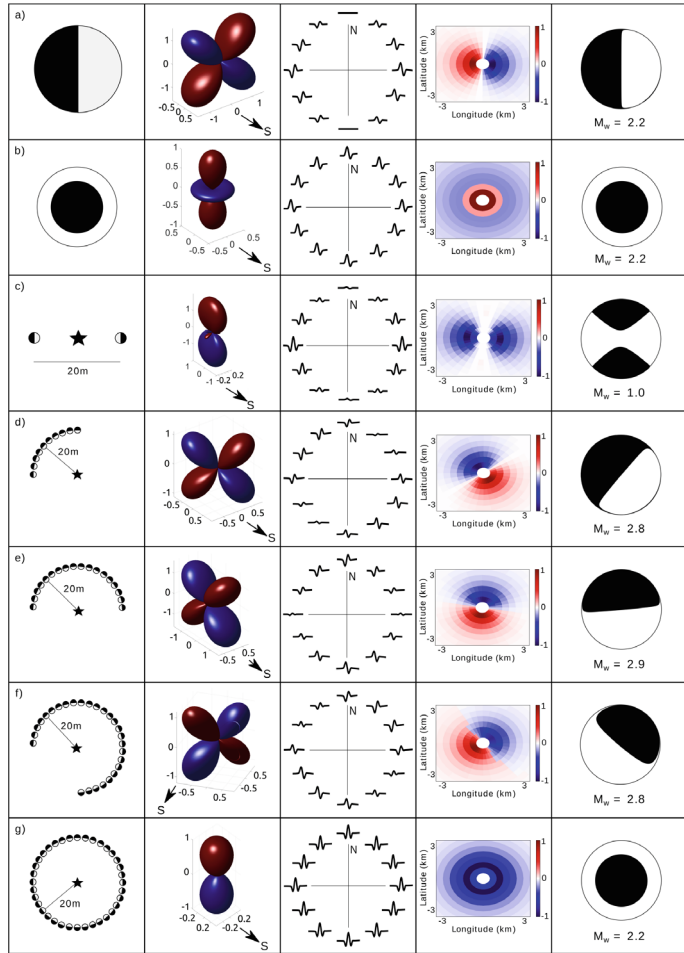


Fig. 7 Comparison of the so called “efficiency” for different rupture shapes. The curvature and the amplitudes produced are anti-correlated, i.e. the more the shape deviates from a planar fault, the less efficiently it radiate energy

of the rupture interfere with each other and the net radiation is smaller than that produced by the planar counterpart. We use the correction factors

obtained by Contreras-Arratia Neuberg (2019) in order to estimate real slip vectors at a ring fault. The radiation of the full-ring rupture, represents only about 2.4% of the net radiation produced by a same-size planar fault, thus, the correction factor is ~ 42 . In the following section we provide a framework to quantify magma ascent and extrusion by using low-frequency seismicity.

3.3 Quantifying Magma Ascent, Amplitudes

From the previous section it is clear that the classic, planar shear rupture is not appropriate to explain the shear rupture occurring at a ring source. In particular, the amplitudes observed and the magnitude estimations need to be corrected

to account for the interference between curved fault sections. Using an empirical relationship between seismic magnitude and slip, we can estimate the displacement of magma at the conduit wall. This will provide insight into the ascent process, whether it is seismic or aseismic, i.e. if the seismicity affects the magma ascent rate or not.

3.3.1 Seismic Moment Estimations

The magnitude estimation of low-frequency events (LP and hybrid events) encounters several complexities, which can lead to a wrong estimation of the real energy release during rupture. The local magnitude scale is not appropriate for these events because it is conceived for brittle failure only. This estimation depends on the maximum amplitude and the duration of the earthquake which scale in a different way. For the case of low-frequency events, the slow tube waves trapped in the conduit produce oscillations for a much longer time. Thus, this scale overestimate the magnitude of the events. In addition, full waveform moment tensor inversions cannot provide a reliable result either, since the low-frequency resonance component does not represent the rupture process itself. In both cases the seismic moment would be overestimated since the source inversion process retrieves a longer source time function than the actual one. However, moment tensor inversion (MTI) studies have been performed on long period events with a pulse-like waveform, which show short durations. In such cases, MTI can accurately estimate the source parameters (Lanza and Waite 2018b; Lokmer et al. 2007; Eyre et al. 2013), however, the waveforms at Soufrière Hills are different showing a clear resonance effect (Neuberg et al. 2000).

To estimate the seismic moments, we calculate the synthetic amplitudes observed in a particular station (MBLG) at a distance of approximate 2 km, where we assume a ring fault to be activated at 1.5 km below the dome. Using the linearity between seismic moment and synthetic amplitude, we can use a least-squares approach to obtain an empirical relationship between these parameters (Eq. 5).

$$M_0 = 9.66 \times 10^{16} \times A_{\max} \text{ [Nm]}. \quad (5)$$

Note that we obtained the value 9.66×10^{16} by considering the ratio of two different synthetic seismic events observed at a single station. This implies that the medium affects both tests in the same way, therefore, the ratio is the same for each station, and needs to be calculated for each station. Hence, we can now relate the maximum amplitude for each event in our event catalogue to the seismic moment of a point source at a certain depth. We then scale the amplitudes to account for the shape of the rupture, i.e. multiplying them by a factor of 42 to account for the ring fault geometry (see Sect. 3.2). Then we estimate the slip at the conduit wall for each event by using an empirical law (Murotani et al. 2013), to derive the individual and total displacements within the conduit, and compare them with the magma volume and its ascent rate, derived in the next section. Here we assumed a ring fault geometry as a source but in principle it could be possible to find the most adequate model amongst full ring fault, 1/2 or 1/4 ring fault, or another geometry, using several seismic observations of a given event and comparing their polarisations with results shown in Fig. 6.

3.3.2 Magma Volume Estimation

Similarly to continuous creep in a tectonic fault zone, where earthquakes contribute only a fraction of the slip along the fault, seismic low-frequency events are only triggered when the continuous magma flow in the conduit reaches a critical velocity such that shear stress overcomes the shear strength of the magma (Eq. 4). In order to link seismicity to magma flux at depth and observed extrusion rate at the surface, we need to estimate this fraction of seismic slip contributing to magma ascent. First we need to link the flux of magma at a certain depth, which is composed of volatiles, crystals and melt to the observed, so-called dense rock equivalent (DRE) of extruded material.

We consider a Poiseuille flow in a cylindrical conduit in which magma is ascending with the velocity profiles shown in Fig. 2. The aim of this calculation is to obtain an approximate value for the magma flux at 1.5 km depth. Note that the depth is measured from the top of the volcano (Neuberg and O’Gorman 2002) to account for the relevant pressure. This corresponds to the source

Table 1 Parameters for conduit flow model

Parameter	Value
Melt density (ρ_{MELT})	2300 kg/m ³
Temperature of magma (T)	1123 K
% of volatiles (n_{TOTAL})	[4.5; 5.5; 6.5]%
Molar mass H ₂ O (M_m)	18.015×10^{-3} kg/mol
Conduit radius (R)	15 m

ρ_{MELT} , T and molar mass are common values for silicic volcanoes. The values for n_{TOTAL} and R are taken from Thomas and Neuberg (2014)

location of seismic events of family A at approximately 500 m below sea level (b.s.l.). The parameters used for the flow models are listed in Table 1.

First we estimate the pressure at depth, assuming the pressure to be the sum of magma-static (lithostatic) plus the excess pressure exerted by the magma reservoir. We approximate the magma-static pressure using the melt density,

$$\begin{aligned} P &= \rho_{\text{MELT}} g h \\ &= 2300 \text{ kg/m}^3 \times 9.81 \text{ m/s}^2 \times 1500 \text{ m} \\ &= 33.8 \text{ MPa}, \end{aligned} \quad (6)$$

where ρ_{MELT} is the density of the melt, g the acceleration due to gravity and h the depth. We assume that the dominant volatile is water given by the range $n_{\text{TOTAL}} = [4.5\%, 6.5\%]$, based on Thomas and Neuberg (2014); this is a first order approximation with large uncertainties. The bulk density ρ_{BULK} is given by (Neuberg and O’Gorman 2002) as

$$\frac{1}{\rho_{\text{BULK}}} = \frac{1 - n_{\text{eg}}}{\rho_{\text{MELT}}} + \frac{n_{\text{eg}}}{\rho_g} \quad (7)$$

where the gas density ρ_g is derived from the ideal gas law, the fraction of exsolved gas n_{eg} from the solubility law for water in rhyolite. Assuming a total water content of [4.5%, 5.5%, 6.5%], the bulk density results in [1337.7; 1115.5; 956.6] kg/m³ and the gas fraction in the range of,

$$\chi = \frac{\rho_{\text{BULK}}}{\rho_g} n_{\text{eg}} = [0.43; 0.53; 0.6]. \quad (8)$$

This shows that for the parameters in Table 1, the volume of magma at 1.5 km depth is around twice the degassed volume observed and measured at the surface (Wadge et al. 2014). This estimation allows us to calculate the magma flux at depth, which is then compared with the cumulative slip

produced by the trigger of low-frequency earthquakes.

3.3.3 Magma Flux

Wadge et al. (2014) have reported daily samples of volume erupted from the volcano during the five stages of the eruption. The values are given in dense rock equivalent (DRE), hence referring to magma completely degassed at the surface, i.e. melt and crystals. The total reported volume is $1.063 \times 10^6 \text{ m}^3$, which over the whole period translates into an average extrusion rate of $4.5 \text{ m}^3/\text{s}$. For this study, we focus on a particular dome collapse event on June 25th, 1997, and the seismicity that led to it. On June 24th and 25th, the erupted material is $0.71 \times 10^6 \text{ m}^3$ and $0.11 \times 10^6 \text{ m}^3$ (Fig. 4), respectively. As we calculated in the previous section, at 1.5 km depth, the gas occupies 50% of the total volume, hence, the value $0.82 \times 10^6 \text{ m}^3$ at the surface is doubled to account for volatiles at this depth, i.e. $1.64 \times 10^6 \text{ m}^3$. For this estimation we use mass continuity, since the melt at surface represents 99% of the total mass; therefore, we do not consider the mass of volatiles exsolved near the surface. Finally, the extrusion is assumed to occur in a time frame of 30 h, thus, we can calculate the displacement of the magma using this time frame and the equation of magma flux $\Phi_{1.5}$ at this depth passing through the conduit,

$$\Phi_{1.5} = \frac{V}{t} = \frac{1.64 \times 10^6 \text{ m}^3}{30 \times 3600 \text{ s}} \approx 15 \text{ m}^3/\text{s} \quad (9)$$

where V is the total volume and t the time. Similarly,

Table 2 Summary of results: seismic moment estimations and slip for each case using 1.5 km depth events

	Point source assumption	Full-ring assumption
Average seismic moment	1.77×10^{11} Nm	7.44×10^{12} Nm
Average seismic slip	$\sim 3 \times 10^{-3}$ m	$\sim 3.8 \times 10^{-2}$ m
Cumulative seismic moment	4.64×10^{13} Nm	1.95×10^{15} Nm
Cumulative slip	~ 0.84 m	~ 10 m

$$\Phi_{1.5} = Av = A \frac{d}{t} \rightarrow d = \frac{\Phi_{1.5} t}{\pi R^2} \approx 2 \text{ km} \quad (10)$$

where A is the cross-sectional area of the conduit, and v the average ascent velocity. This result shows that magma moved 2 km upwards to finally emplace $0.82 \times 10^6 \text{ m}^3$ of material at the surface. In addition, we see in Fig. 2, that magma at the centre of the conduit moves faster than at the boundaries, therefore, the biggest contribution to the volume extruded is through its centre. The material ascending near the conduit wall is a small percentage of the total movement. We will inspect in the following whether the co-seismic slip at the conduit boundaries is important or irrelevant for the overall ascent.

3.3.4 Full-Ring Slip Estimations

So far, we obtained the net ascent of the magma column which explains the magma extrusion measurements provided by Wadge et al. (2014), but, how important is brittle failure in magma during this process? Can we effectively estimate the magma extrusion from observed high-frequency phases in low-frequency seismicity?

We use the linear relationship between the maximum amplitudes observed at a particular station in Montserrat (MBLG) and the seismic moment of a full-ring rupture (Eq. 5) to obtain an estimation of the seismic moment assuming a single station amplitude. It is important to note that Eq. (5) holds for a particular station, studies in other volcanoes/stations need to consider other source-receiver configurations. By using the empirical relationship found by Murotani et al. (2013) (Eq. 11) we can calculate the slip (D) at the fault for each event. Later, we calculate the seismic moment and the slip for a full-ring rupture by applying the corresponding correction factor of 42

as explained above. The results are summarised in the following Table 2 for a depth of 1500 m below the dome.

$$D = 1.66 \times 10^{-7} M_0^{1/3} \quad (11)$$

The main conclusions from this section are:

- The slip values obtained for each event on a full-ring rupture are consistent with geological observations made by Tuffen et al. (2003) in Torfajökull volcano, Iceland. The authors measured faulting processes in an exhumed dyke which shows slip values of the order of centimetres.
- The area of rupture is constant through the process since the seismicity is stable, i.e. the same location and the same source; therefore, each rupture occurs within the section of magma that takes the position of the previously fractured section. Tuffen et al. (2003) and Neuberg et al. (2006) also considered the effect of healing of the fractured magma. Due to the high temperature, the evolution of the system can be intermittent between fracturing and healing processes, this is a plausible scenario since the temporal separation of these events is less than 3 s and long enough for the magma to heal.
- We conclude from the results in Table 2 that the cumulative slip over 30 h (≈ 1 –10 m, depending on the size of slip surface) is very small compared to the total ascent of the entire magma column (≈ 2000 m). Hence, magma ascent is mainly ‘aseismic’ in the sense that seismic slip on the conduit wall contributes little to overall magma ascent at this depth where magma still behaves as a fluid.

For the depth where LP seismicity is detected, we have to separate two flux regimes; the first and most dominant is the flow ascending through the

centre of the conduit where the magma behaves as a fluid resulting in an average velocity of 2×10^{-2} m/s. At the thermal boundary layer, near the conduit walls, a high temperature gradient promotes crystallisation and an increase in magma viscosity, two effects that, in turn, stimulate brittle failure. The ascent velocity within this layer is slower and tends to zero at the walls (Fig. 2). If the magma moved by the rate of seismicity alone, it would ascend at 9×10^{-5} m/s. This comparison gives an idea about how little of the flow motion is transferred into seismic energy for an average volcanic earthquake, an amount about 200 times smaller than the actual magma ascent rate. This ratio is not a result that can be generalised, but needs to be determined for each volcanic setting and applied to different station configurations. However, once calibrated, we can use this ratio between magma ascent velocity and slip to estimate magma extrusion from LP seismicity alone, where brittle failure of magma is triggering low-frequency earthquakes.

4 VLPs

4.1 Introduction

The deployment and widespread use of broadband seismic networks in the 1990s made studies of very-long period (VLP) signals possible (Kawakatsu et al. 1992; Neuberg et al. 1994). VLP signals, whose periods range from tens to several hundreds of seconds, have been observed on almost every type of volcano around the world (Chouet and Matoza 2013). The studies of VLP seismicity have resulted in a much improved understanding of the shallow magma conduit geometry, of the way magma moves through shallow volcanic systems, and the interaction between magma and magmatic gasses and the host rock (Waite 2014).

Unlike LP signals, which are generally interpreted as a resonance inside the fluid-filled conduit, VLP source processes are usually attributed to fluid-rock interactions such as mass movement of volcanic fluids (e.g. Chouet and Dawson 2011) that generate abrupt pressure changes inside the volcanic edifice. As VLPs have been observed

prior to caldera collapse (Kumagai et al. 2001; Michon et al. 2009) and prior to phreatic eruptions (Kawakatsu et al. 2000; Jolly et al. 2017) the need to study them is of great importance for understanding the underlying physical processes, and therefore, assess the potential hazard. The major advantage VLP signals offer is a direct insight in the deformation process within the source region. This fact was recognised and studied by Legrand et al. (2000, 2005). The fact that VLP signals have wavelengths of tens to hundreds of kilometres, places most seismic stations of a volcanic monitoring network in the so-called near-field, i.e. within one wavelength from the source. In the near-field, the seismic displacement at the surface is directly proportional to the deformation at the source. Therefore, it is essential to retrieve the exact source time history in addition to amplitude and moment tensor components to adequately model the deformation process.

4.2 Practical Tips to Find VLPs in Monitoring Data

Although some VLP seismicity can be seen clearly on broadband seismograms (e.g. Jolly et al. 2017; Caudron et al. 2018), other VLP signals cannot be easily identified on a broadband velocity seismogram. This is due to the instrument itself acting as a “differentiator” as ground displacement is converted to velocity, i.e. the instrument itself acts as a high-pass filter suppressing the low and enhancing high frequencies. Therefore, the first step in searching for a VLP signal is analysing the amplitude spectrum of the recorded velocity seismogram. In Fig. 8a, a VLP signal observed on Soufrière Hills volcano (SHV), has a broad peak around 0.01 Hz. However, the spectrum of this VLP signal has been distorted by the instrument response as the lower frequencies in the original signal have been cut-off. Hence, when analysing VLP signals that have a frequency content outside the flat-band of the instrument response, one needs to keep in mind the original signal could contain seismic energy at much longer periods than displayed in the amplitude spectrum of the recorded signal.

Figure 8b shows such an example where a signal with dominant period of 500 s is observed at a station with a 120 s instrument.

Another simple way to identify a VLP signal when it is not directly observable on the velocity seismogram is to integrate the velocity seismogram or apply a low-pass filter. Figure 9a shows a 16 min long record of the VT swarm observed on March 23rd 2012 on SHV. The velocity seismogram is dominated by the high frequency VT earthquakes. However, if we integrate the seismogram (Fig. 9b) the VLP signal becomes obvious. In this case we see two clear VLP signals, one starting at 07:16 UTC and the other one, with much larger amplitude, at 07:19 UTC.

4.3 Recipe for VLP Processing: Restitution of Ground Displacement

To reverse the effect of the instrument response by the restitution of ground displacement considering the whole energy content of the original signal certain processing steps are required. These processing steps go beyond the usual “instrument removal” applied as a routine tool by seismic processing packages, which considers the frequency range in the pass-band of the instrument only. Figure 9 shows the restitution of vertical ground displacement of a VLP signal observed during an outgassing event at Montserrat using a 120 s Güralp-3T broadband instrument. This example shows how these processing steps can influence our interpretation of the source dynamics.

For the process of restitution, different high-pass filters are applied to the velocity trace. The application of a high-pass filter with a cut-off frequency lower than the flat-band of the instrument response (Neuberg and Luckett 1996; Caudron et al. 2018; Sindija et al. 2021) allows us to recover the low frequency information while suppressing the amplification of the long period, environmental and electronic noise during the integration. Choosing the appropriate cut-off frequency of the high pass filter is crucial, as the interpretation of the obtained displacement seismograms changes and therefore our interpretation of the source

behaviour changes as well. In this case, cut-off frequencies of 0.004 Hz (250 s), 0.002 Hz (500 s), and 0.001 Hz (1000 s) are applied. Afterwards, the instrument response (including the digitiser gain) is removed and the trace is integrated to obtain the displacement seismogram.

The displacement seismogram in Fig. 9c shows an apparent inflation (motion up) followed by a deflation (motion down) below the pre-signal level. This interpretation dramatically changes by including longer periods in traces (d) and (e). The difference in waveforms between trace (d) and (e) demonstrates that the residual effect of the instrument transfer function could have been interpreted as a complex source behaviour of inflation and deflation. The ground displacement shown now in trace (e) could be described as a step-like inflation. The fact that a further extension to an even lower frequency range does not change the waveform indicates that the trace now represents the “true” ground displacement of the process. In this case it gives us the “true” amplitude of the displacement as well, which can be directly read from the displacement seismogram (Fig. 9f).

Unfortunately, there is no general criteria how to define the lowest cut-off frequency as this process is highly dependent on the data quality and seismometer transfer function. As shown in Fig. 9, extending the cut-off period from 500 to 1000 s still results in a change of the corresponding displacement waveforms, hence, 1000 s seems here an appropriate choice of a maximum filter cutoff. Only if even higher cutoff periods produce the same waveform, one can assume that no smaller frequencies (larger periods) are contained in the signal given the frequency limits of the seismometer in use.

In general, the vertical components are less affected by low frequency noise than the horizontal components, which can be affected by tilt. In this case we follow the procedure by Wielandt and Forbriger (1999) and assume that the horizontal components have the same source time function as the (tilt-free) vertical component. Hence, one can distinguish between the horizontal ground motion—following the source time function—and the additional tilt contribution, that can be removed.

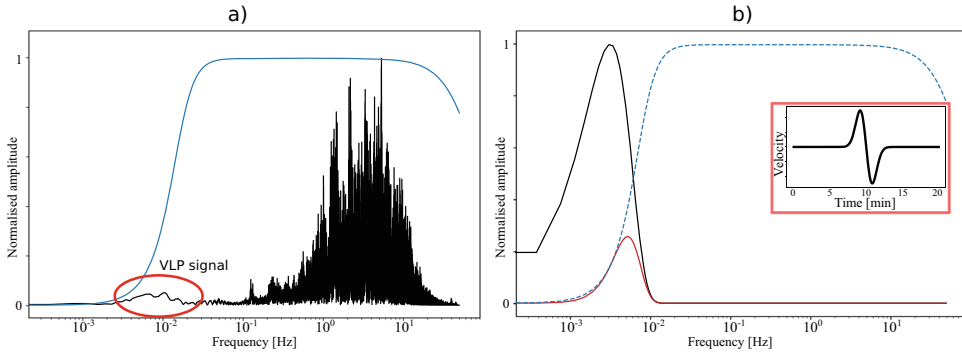
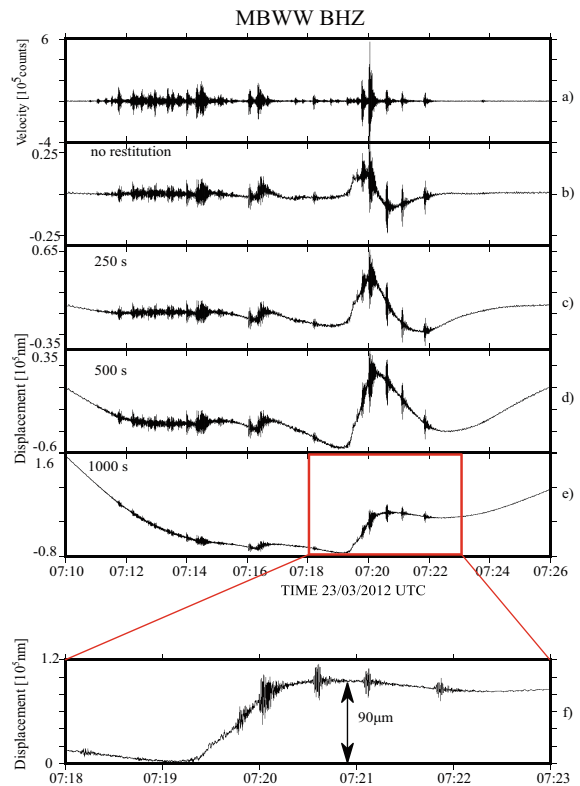


Fig. 8 **a** Amplitude spectrum of the vertical component velocity seismogram recorded at MBWW station on March 23rd, 2012 showing a broad VLP signal with dominant frequency of 0.01 Hz with superimposed transfer function of a 120 s-instrument at that station. **b** Example of how the

instrument response (blue) impacts the observed amplitude spectrum; synthetic velocity seismogram with period of 500 s (inset) and corresponding amplitude spectrum of the original signal (black), resulting spectrum (red) after multiplication with the instrument response (blue dotted)

Fig. 9 Restitution of the vertical component ground displacement at MBWW station of the event on March 23rd, 2012 (Fig. 8a). **a** Uncorrected velocity seismogram. **b** Integrated (without restitution) velocity seismogram which identifies the VLP signal. Displacement seismograms after correcting for the instrument response and considering periods of up to 250 s (**c**), 500 s (**d**) and 1000 s (**e**), respectively. **f** Five minute long time window showing true ground displacement. Adopted from (Sindija et al. 2021)

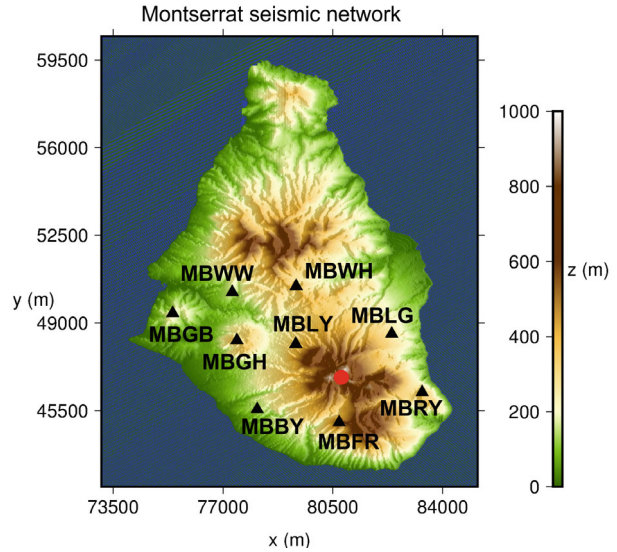


5 Moment Tensor Inversion

Moment tensor inversion (MTI) is a powerful tool to obtain a full picture of the seismic source process. It is particularly important on volcanoes where contributions to the source process other

than double-couple components are caused by the volcanic plumbing system. Regarding many aspects of MTI like the influence of topography, the velocity model including the impact of shallow low-velocity layers, MTI and source locations

Fig. 10 Seismic network on Montserrat in 2012 and source epicentre (red circle)



we refer the reader to an extensive body of literature, e.g., Chouet et al. (2003a), Bean et al. (2008), Dawson et al. (2011), Thun et al. (2015). In contrast we want to emphasise two aspects here that are often neglected or overlooked in volcano observatories: (i) the fundamental difference of a successful fit of seismic waveforms compared to a good fit of source parameters (MT components), and (ii) how to assess the important influence of the seismic network design on the MTI results.

Lanza and Waite (2018a) tested the ability of 16 synthetic seismic networks with the number of stations ranging from three to 40 to resolve the key components of the moment tensor. As a case study they use Pacaya volcano, Guatemala for which they computed synthetic seismograms for six input source models—(1) a dipping crack, (2) a vertical crack, (3) an isotropic source, (4) a pure compensated linear vector dipole (CLVD), (5) a linear vector dipole (LVD), and (6) a double-couple (DC). Their study focused on the number of seismic stations and major findings show that the similar level of uncertainty is found for networks with as many as 40 stations as it is in networks with only eight stations. In contrast, we use the existing seismic network at Soufrière Hills volcano (SHV) in 2012 as a case study to estimate the influence of the seismic network configuration on the resolved moment tensor components. Multiple moment-tensor inversions were

performed and some stations were taken out to see how well different source mechanisms could still be obtained simulating a volcanic crisis with decreasing data coverage. On the other hand stations are strategically added to the existing network in order to enhance the azimuthal coverage. Vertical DCs with varying strike directions are employed as input sources to simultaneously reveal the influence of the source orientation on the resolved moment tensor.

In these tests, first the forward problem is solved by calculating synthetic seismograms for a source with a certain orientation and depth. Then a moment tensor inversion is performed and the inversion results are evaluated in two ways: how well do resolved seismograms fit the forward model (*fit of seismograms*) and how well does the inversion resolve the input source time history, i.e. time history of the moment tensor components (*fit of source parameters*).

Furthermore, we show that, depending on the station configuration, one can obtain a good fit of seismograms, while the results for the source mechanism do not converge to a unique solution. Using these moment-tensor resolution tests observatories could analyse their existing station configuration and enhance their ability to correctly invert for moment tensors by adding a station at a certain location.

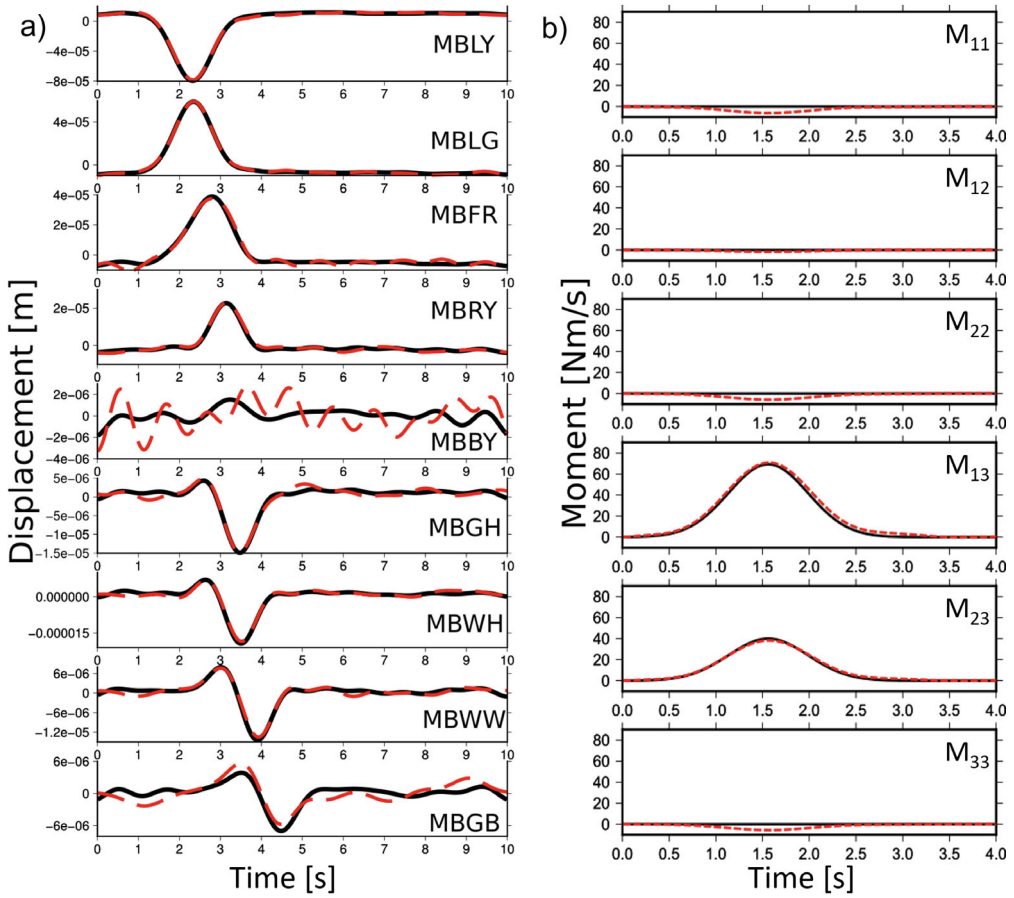


Fig. 11 MTI using 9 station configuration showing: **a** Comparison between vertical surface displacement of forward model (black) with inversion result (dashed red)—*fit*

of seismograms. **b** Resolved time histories for the MT components (dashed red) compared with the time histories of the forward model (black)—*fit of source parameters*

5.1 Station Coverage

The MVO seismic network in 2012 consisted of nine stations equipped with three-component broadband seismometers (Fig. 10). Water Works (MBWW) station, deployed by the University of Leeds, Broderick's Yard (MBBY), Windy Hill (MBWH), Fergus Ridge (MBFR), Garibaldi Hill (MBGB), St. George's Hill (MBGH), Long Ground (MBLG), Lee's Yard (MBLY), and Roche's Yard (MBRY).

To see how well we can resolve a source model using different station configurations, the numbers of stations used in the inversion is varied. The source was placed below the volcano summit at 1000m below sea level (b.s.l.). The input source time history is described using a

Gaussian function with a period of 3 s. The source used for calculating synthetic displacements is a pure vertical slip with a moment magnitude (M_0) of 10^{12} Nm, dip (δ) 90° , rake (λ) 90° , and strike (ϕ) of 60° . The displacement seismograms are calculated for two scenarios—(1) when all nine stations (27 components) are operational and (2) an “eruption” scenario where only the four most distant stations (12 components) north-west of the volcano are operational (MBGB, MBGH, MBWH, MBWW). Figure 11 shows the results for the first scenario where all the stations are operational. As expected, forward model and inversion results show good agreement when comparing resulting seismograms (Fig. 11a) and source parameters (Fig. 11b). The only

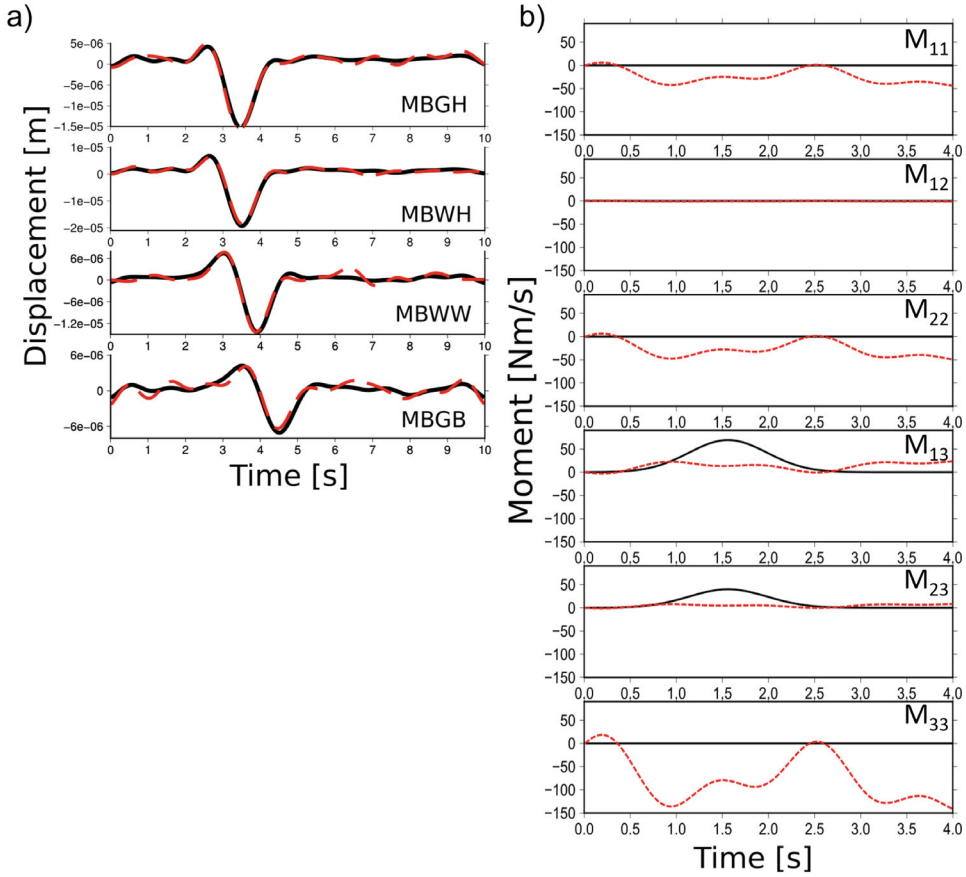


Fig. 12 MTI using 4 station configuration showing: **a** Comparison between vertical surface displacement of forward model (black) with inversion result (dashed red)—*fit*

of seismograms. **b** Resolved time histories for the MT components (dashed red) compared with the time histories of the forward model (black)—*fit of source parameters*

exception is station MBBY which is close to the nodal plane; note, only vertical components are depicted, while all components were used for the MTI.

We obtain a different picture for the second scenario where only the four most distant stations are used (Fig. 12). Seemingly, the fit at the surface (a) is perfect, however, when we look at the fit at the source, the MT components are not resolved at all. This reveals that we should not trust the results from just the ‘seismogram’ fit often presented in publications as evidence since it does not guarantee the choice of the correct model for a non-unique problem.

A common methodology for finding the best solution of the moment tensor inversion is based on minimising a weighted square misfit between the observed and resolved data (e.g. Ohminato et al. 1998; Chouet et al. 2003b; Cesca and Dahm 2008):

$$\text{misfit} = \left[\frac{\sum_{i=1}^{N_t} \sum_{j=1}^{N_i} (d_i(t_j) - s_i(t_j))^2}{\sum_{i=1}^{N_t} \sum_{j=1}^{N_i} (d_i(t_j))^2} \right], \quad (12)$$

where N_t is the number of time traces, N_i is the number of time samples for i -th trace, and $d_i(t_j)$ and $s_i(t_j)$ are the j -th samples of i -th time trace for input data and synthetic time trace, respectively (Cesca and Dahm 2008). The misfit results are dimensionless and normalised. As a consequence of the misleading similarity in seismograms as shown in the previous example we suggest to use, for network testing, the misfit between forward model and resolved MT components instead.

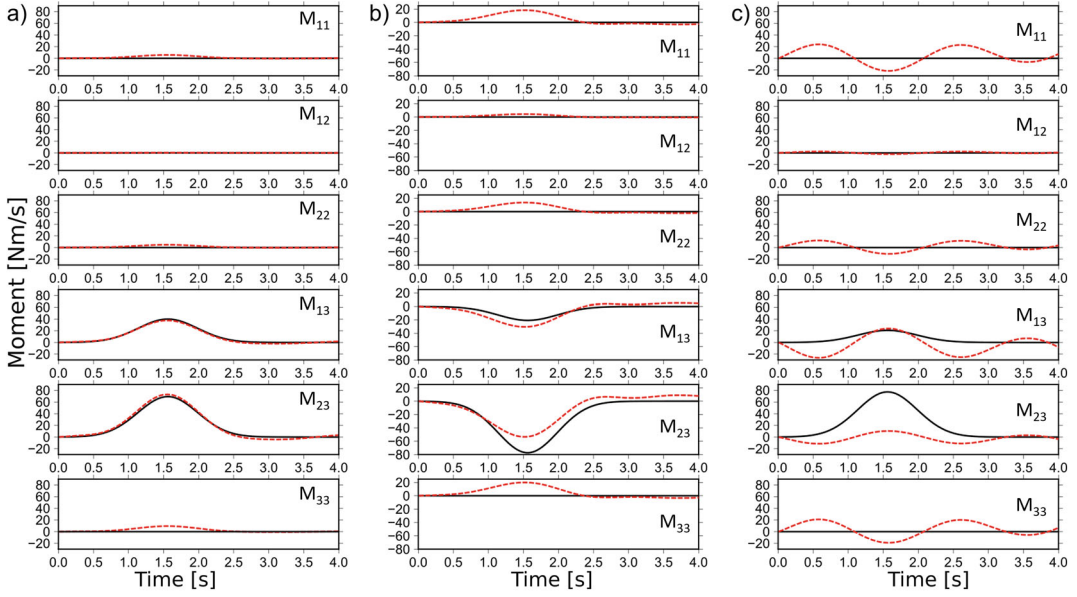


Fig. 13 Resolved MT components (red dashed) for three input models (black) at 0 m depth with varying strikes: **a** strike = 30° with misfit = 0.02, **b** strike = 195° with misfit = 0.3, **c** strike = 15° with misfit = 1.2

5.2 Influence of Source Depth and Orientation

In the next step we test the influence of source depth and orientation on the MTI results. The sources are placed at three different depths; 0, 500, and 1000 m below sea level (b.s.l.). The source mechanism is again a vertical slip DC, with $M_0 = 10^{12}$ Nm where the strike angle is varied between 0° and 195° in 15° intervals. Firstly, the tests are done using the seismic network of nine stations and we focus on three different strike directions for the source at depth 0 b.s.l.

Source model 1, 2, and 3 have strike directions (ϕ) of 30°, 195°, and 15°, respectively. The choice of strike directions will produce, for the Montserrat network, three increasing values of misfit calculated using (12).

$$M_{\text{model 1}} = \begin{bmatrix} M_{11} & M_{12} & M_{13} \\ M_{21} & M_{22} & M_{23} \\ M_{31} & M_{32} & M_{33} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0.5 \\ 0 & 0 & 0.866 \\ 0.5 & 0.866 & 0 \end{bmatrix} \quad (13)$$

$$M_{\text{model 2}} = \begin{bmatrix} M_{11} & M_{12} & M_{13} \\ M_{21} & M_{22} & M_{23} \\ M_{31} & M_{32} & M_{33} \end{bmatrix} = \begin{bmatrix} 0 & 0 & -0.259 \\ 0 & 0 & -0.966 \\ -0.259 & -0.966 & 0 \end{bmatrix} \quad (14)$$

$$M_{\text{model 3}} = \begin{bmatrix} M_{11} & M_{12} & M_{13} \\ M_{21} & M_{22} & M_{23} \\ M_{31} & M_{32} & M_{33} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0.259 \\ 0 & 0 & 0.966 \\ 0.259 & 0.966 & 0 \end{bmatrix} \quad (15)$$

For source model 1, 2, and 3 the calculated misfits are 0.02, 0.3, and 1.2, respectively. It is important

to note the “leakage” into diagonal components of the moment tensor (M_{11} , M_{22} , M_{33}) for source model 2 (Fig. 13b). The diagonal components are part of the isotropic part of the moment tensor and wrongly indicate a volume change at the source. The MT component of source model 3, with the highest misfit, are not resolved at all (Fig. 13c).

To display the full range of our model space the results are colour-coded based on the calculated misfits. We suggest a colour code system where the results are marked as green for a misfit below 0.1, indicating that the source components are resolved correctly. For misfits between 0.1 and 0.8 results are marked in yellow to orange, suggesting caution in interpreting these results, and everything above 0.8 is coloured red warning that those results should not be trusted.

The source orientations for which we can resolve the MT components, or not, can now be mapped (Fig. 14) for all three examined source depths. We can immediately see the depth dependence of the results; for the source depth of 1000 m b.s.l. we can resolve correctly the MT components for all strike angles. However, for shallower depths the source orientation plays a defining role.

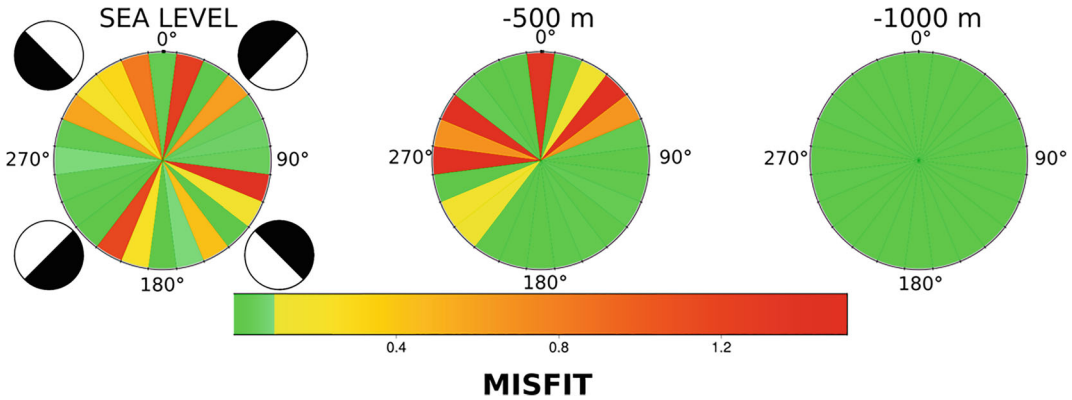


Fig. 14 Quality map of MTI for nine stations and three different source depths. For misfit below 0.1 the results are marked in green, between 0.1 and 0.8 they are marked from yellow to orange, and everything above 0.8 in red

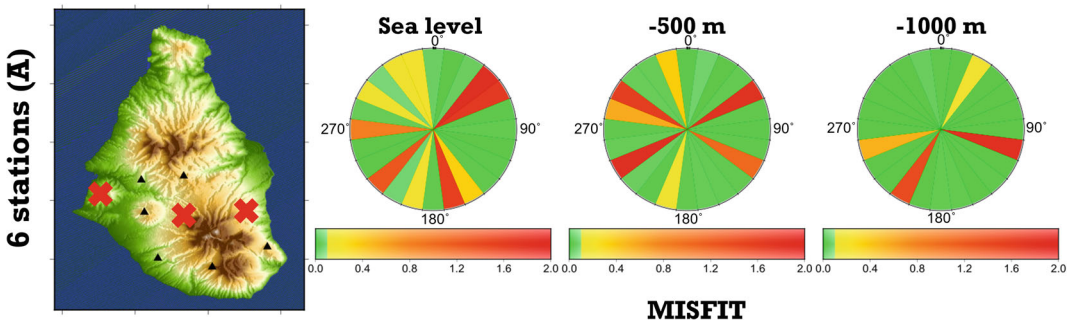


Fig. 15 Quality map of MTI for six stations with the same colour code as above. Red crosses depict stations taken out by an ‘eruption’

5.3 ‘Eruption’ Scenarios

An important consideration for volcano observatories is to reflect on their abilities to determine moment tensors in an eruption scenario where the number of usable seismic stations could be reduced. Using our colour code framework of testing seismic network configurations we reduce systematically the number of stations used in the inversion. The results are shown for three different station configurations, one with six stations that shows clear signs of a deteriorating of performance (Fig. 15) and two with only four stations (Fig. 16).

Unsurprisingly, reducing the number of stations even further leads to inferior inversion results. Figure 16 depicts two scenarios with very different azimuthal coverage. If the number of stations is kept constant, and just one station (MBGH) is swapped with another (MBRY) on the

other side of the volcano the results are improved, especially for larger depths. This shows the influence of azimuthal coverage on the moment tensor inversion. Lanza and Waite (2018a) report that in their tests for the station configurations which have maximum azimuthal gaps between adjacent stations less than 130° they were able to obtain better results than for configurations with the same number of stations but larger azimuthal gap. Similarly, we see here that when adding a station which is $\approx 180^\circ$ away from its adjacent stations we can considerably enhance the ability to correctly resolve MT components.

5.4 Testing Network Performance

We suggest that this framework can be used to test the performance of a seismic network when planning a network or improving an existing network

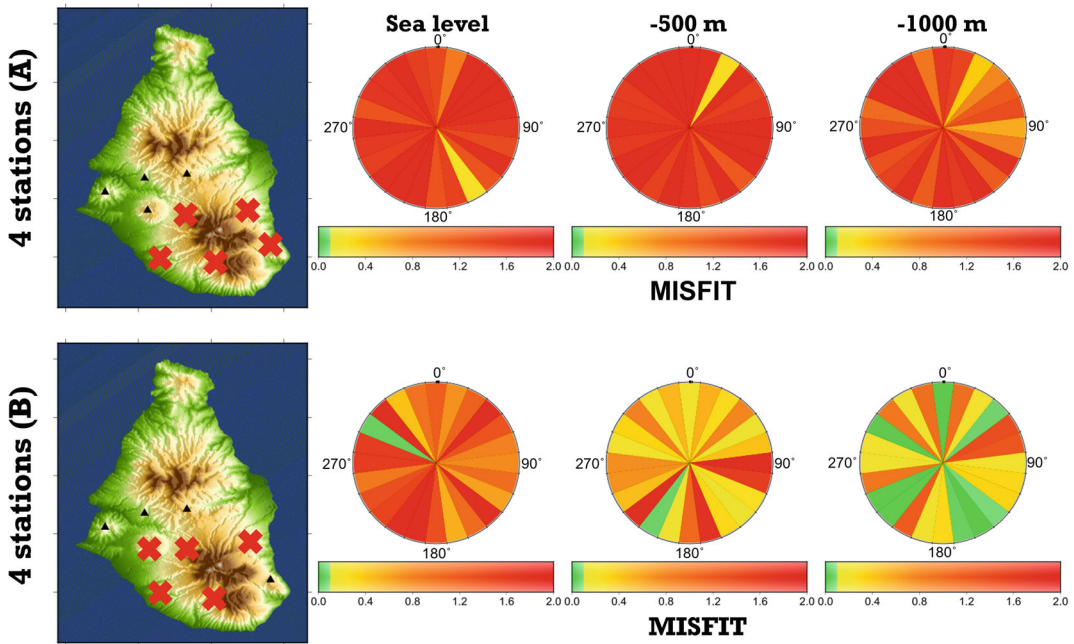


Fig. 16 Quality map of MTI for four stations with the same colour code as above. Red crosses depict stations taken out by an ‘eruption’

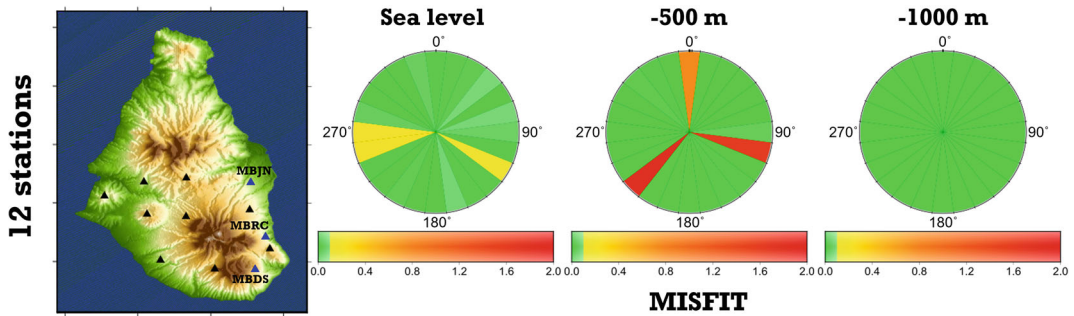


Fig. 17 Improvements to the seismic network. The original station configuration is represented using black triangles and the three new stations (MBDN, MBRC, MBDS) are represented with blue triangles. There is a general improve-

ment of the results, except for two strike angles for the source at sea level ($\phi = 120^\circ$ and $\phi = 255^\circ$) and at 500 m b.s.l. ($\phi = 105^\circ$ and $\phi = 225^\circ$)

by adding stations. This includes to consider vital communication links between stations and observatory. In the following we add three stations to the Montserrat reference network used before to further investigate the influence of azimuthal coverage. The original seismic network configuration (Fig. 10) has only two stations (MBRY, MBLG) east of the volcano, therefore the azimuthal coverage is not ideal. For this reason three stations on the eastern part of the island are added—MBDS,

MBJN, MBRC (Fig. 17). As expected the results are improved drastically when compared to the Montserrat reference network (see Fig. 13). Note that this is not the case for all strike directions.

While we demonstrated this with MTI, a similar framework could be applied for the ability of the network to locate local volcanic earthquakes.

6 Checklist for Volcano Observatories

Instead of having a final section on conclusions we summarise our findings from this chapter by suggesting a checklist of 10 points which might be helpful for volcano observatories or anybody else performing monitoring tasks on an active volcano. According to the main theme of this chapter, this checklist focuses on monitoring of LPs and VLPs on volcanoes with high viscosity magmas, but addresses also more general topics of seismic networks design.

- i. Rather than considering the general level of seismicity by looking at RSAM, separating different seismic signals at least into VTs, LPs and other distinct species is essential as each type represents a different volcanic process. The absence of VTs within a part of the volcanic edifice can be as significant as the occurrence of a swarm. Modern methods using Artificial Intelligence (AI), Machine Learning and General Pattern Recognition can assist to automate data processing and allow event classification in near real time.
- ii. When identifying and isolating LP events, it is worthwhile to look on a deeper processing level for similar, repeating waveforms, referred to as event families. Again, they can be interpreted in a specific way indicating a stationary source location, pointing to stick slip motion or brittle failure of a magma column which offers the opportunity to link seismicity to magma ascent rate. This link is specific to a silicic volcanic setting and in most cases also to a certain time period of eruption and needs, therefore, specific and renewed calibrations.
- iii. If swarm activity of LP events is used to detect acceleration of magmatic activity, e.g. using the Failure Forecast method (FFM), it is prudent to apply this method to an individual event family only, rather than combining different event locations or even considering RSAM. Magma movement at each event location is considered a separate ‘system’ that accelerates through time and behaves according to the material failure criterion. Combining two or more ‘systems’ can blur the point in time when a critical acceleration is reached. The difficulty of applying this method in near real time is that algorithms for automated event detection and analysis need to be set up, calibrated and tested well in advance of a seismic crisis while one has to assume that data characteristics between the training phase and crisis remain similar.
- iv. LP swarms can merge completely into tremor such that the separation of a single event is not longer possible. In this case it might be helpful to extend the detection time window and search in the spectral domain for characteristic features like spectral lines. If the events are regularly spaced in time they will appear as lines in the spectrograms of all stations and the distance between lines corresponds to the inverse event rate. Unless the spectral lines are site specific and caused by site effects, the distance between the lines can therefore be interpreted as related to event rates, even in merged seismic swarms.
- v. Unlike the determination of a seismic radiation pattern that assumes faulting on a plane, a full moment tensor inversion (MTI) is a powerful tool that gives insight into the origin of an earthquake including volumetric components that can be linked to magmatic processes. When assessing the error in the inversion we showed in our synthetic study that a good match of waveforms does not necessarily translate into a successful inversion of moment tensor components at the source. Further caution is advised in interpreting amplitude and time history of seismic source parameters where complex fault planes in a volcanic plumbing system might be involved in the generation of volcanic earthquakes. While curved fault planes yield amplitudes that are always smaller than those obtained from planar faults, the waveform looks like the time derivative of the original signal, hence, displacement appears to be velocity. This can lead to wrong conclusions regarding magma movement where magma

ascend appears to be an up and down movement of magma in the conduit.

- vi. The availability of modern broadband seismic sensors with high dynamic range was an important game changer in volcano seismology as they match the broad frequency and amplitude range of volcanic seismic signals. Ideally, a minimum of three broadband sensors should be deployed on a volcano in the near field but a single sensor is still better than none at all. Due to the wide frequency and amplitude range, the seismogram from a broadband sensor is often not suitable to be displayed in a way resembling the old-fashioned 'drum-plot' which is very handy to obtain a quick overview of the real-time seismicity. As a consequence, high-pass filters are applied to smoothen the traces and the broadband characteristic of the monitored signal is lost. Furthermore, entire broadband seismic networks are sometimes used to merely locate and count seismo-volcanic signals without using the broadband waveform for further analysis. It goes without saying that this constitutes a waste of resources as such basic analysis could be performed by using much cheaper, short-period, even single-component instruments.
- vii. If further waveform analysis is the goal and VLPs are on the agenda, these type of events are often hidden in the seismogram. Even though no high-pass filter is applied the band-limited seismometer transfer-function prevents easy detection of seismic energy below the cut-off frequency of the instrument. In this case, we suggest either a routine application of a low-pass filter or a simple numerical integration of the incoming seismogram. Using an amplitude log-scale when performing the spectral analysis can also help to identify VLP signals. In most cases these procedures will reveal if there is any low-frequency energy content in the seismogram below the instrument pass-band, or not.
- viii. Once a VLP is detected it is worthwhile to check if, after integration, the resulting displacement corresponds to the true ground motion at the recording site, or if the trace is still distorted by the impact of the seismometer response. This so-called restitution process involves the careful application of a high-pass filter and the inverse filter of the instrument response, before the final step of integration can reveal the true ground motion. We routinely included low-frequency spectral contributions down to 1000 s period from a 120 s instruments. It is best to start with the vertical component, followed by the horizontal components which contain usually more low-frequency noise. This restitution process often reveals a much simpler waveform in the displacement than the untreated seismic trace would suggest.
- ix. When designing a seismic network from scratch or upgrading an existing network, it provides a good opportunity to carry out synthetic tests to optimise the capability of a seismic network to perform moment tensor inversions. Here the sensitivity to focal depth and fault orientation is important as demonstrated in this chapter. The same principles apply to seismic source locations where an even lateral instrument coverage is not necessarily the optimal solution. L-shaped seismic arrays or so-called seismic antennas where seismometers are deployed in dense clusters and event locations are determined by beam forming could be a good alternative, particularly where a uniform instrument coverage is not possible.
- x. A second set of criteria regarding the network design should be dedicated to the robustness of data acquisition during a volcanic crises when several seismic stations in close proximity to an eruptive vent could be knocked out completely or tele-communication between stations and an observatory is interrupted. Examples of good practice include redundant communication links where a choice of several repeaters allows to redirect signals via alternative routes and robustness of technology is preferred to more sophisticated but also more vulnerable solutions. During volcanic crises, restricted serviceability of a network

and the design of a minimum station configuration to maintain and perform essential tasks need to be anticipated and planned for.

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Network-Based Analysis of Seismo-Volcanic Tremors

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Abstract

Volcanic tremors represent one of the most important class of seismo-volcanic signals due to their abundant presence in seismic records, their wealth of information regarding magmatic systems, their use as a tool for monitoring the state of volcanoes and their potential as precursor signals to eruptions. These signals have been analyzed for several decades with single station approaches, from which empirical inferences can be made regarding their sources, generation mechanism and scaling relations with eruptions parameters. Modernisation and densification of instrumentation networks coupled with sophistication of analysis methods and enhanced computation capacities, allow to switch from single-station to full seismic network based methods. We introduce in this chapter the inter-station cross-correlations methods, the estimation of the network covariance matrix and

the study of its eigenvalues and eigenvectors. Such advanced methods enable to measure temporal, spatial and spectral tremor properties. They are contained in the CovSeisNet Python package which has been used for characterizing various tremor episodes, including two examples from Kilauea volcano, Hawaii and Klyuchevskoy Volcanic Group, Kamchatka presented in this chapter. These application examples illustrate the complexity of tremors and emphasize the need to continue the development of new algorithms aimed at the exploration of network covariances to better constrain the different tremor generation processes that can be multiple, simultaneous and interacting. In particular, the combination of network-based analysis with polarization and machine learning approaches may represent a new step in our understanding of the underlying phenomena. In turn, this enhanced discernment of the involved processes and the links with the properties of the volcanic system can lead to a more effective monitoring and ultimately a better apprehension of volcanic system destabilizations and anticipation of the associated unrests.

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1 Introduction

Active geological and environmental processes produce various seismic signals. In addition to impulsive events corresponding to regular earthquakes, weak nearly continuous signals

without clear onset are recorded by seismographs in different environments and are known as seismic tremors. So far, seismic tremors have been reported in association with volcanoes (e.g., Konstantinou and Schlindwein 2002; Chouet and Matoza 2013), seismogenic faults (e.g., Obara 2002; Nadeau and Dolenc 2005), glaciers (e.g., Podolskiy and Walter 2016), geysers (e.g., Kedar et al. 1996, 1998), geothermal fields (e.g., Leet 1988; Gudmundsson and Brandsdóttir 2010) and rivers (e.g., Burtin et al. 2011; Gimbert et al. 2014).

Volcanic tremors form the most prominent class of signals in terms of their duration recorded by seismometers installed in the vicinity of active volcanoes. They represent seismic records of continuous or nearly continuous ground vibrations with durations from minutes to months. Signals classified as tremors are recorded at most active volcanoes in association with eruptions and their preparatory phases, and sometimes during inter-eruptive periods. For this reason, tremors are one of the main focuses of volcano seismology and are used by many volcano observatories to monitor and forecast volcanic activity. Another reason for the strong interest in tremors is that the origin of most of them is believed to be directly related to processes occurring in the magmatic feeding systems. Therefore, studying the variations in the properties of observed tremor signals potentially might help us to understand how the magma is stored and migrates beneath volcanoes, which is one of the main goals of volcanology.

For the above mentioned reasons, the volcanic tremors have been extensively studied with more than 1,000 scientific papers being published on this topic up to date (Zobin 2011). Nevertheless, despite such strong attention, many aspects of volcanic tremors remain not well understood. The main reason for this is the complexity of the phenomena. Indeed, volcanic tremor is not just one very specific type of signal produced by one specific phenomena, but a very broad (and not exactly defined) class of signals. These include: co-, pre- and inter-eruptive tremors; shallow and deep tremors; harmonic and spasmodic tremors; short-, long- and very-long-period tremors; gliding tremors, etc. Amplitudes, durations, and

frequency contents of these signals are very variable. Extended reviews of properties of volcanic tremors observed at many volcanoes can be found in several dedicated papers and textbooks (e.g., McNutt 1992; Konstantinou and Schlindwein 2002; Chouet 2003; McNutt and Nishimura 2008; Zobin 2011; Wassermann 2012; Chouet and Matoza 2013).

A variety of physical mechanisms has been suggested to explain the generation of seismo-volcanic tremors. Most of them are associated with the magmatic and/or hydrothermal fluids. A non-exhaustive inventory of those includes: fluid-driven cracking (e.g., Aki et al. 1977; Aki and Koyanagi 1981), resonance of magma filled chambers, conduits, and cracks (e.g., Chouet 1996), nonlinear excitation by a non-stationary fluid flow (e.g., Julian 1994), reaction force from ejected magma (Nishimura et al. 1995), magma-wagging oscillation (Jellinek and Bercovici 2011), non-stationary transfer of gases through a permeable cap (Girona et al. 2019), magmatic-hydrothermal interactions (Matoza and Chouet 2010), magma degassing (Melnik et al. 2020), etc. Alternatively, frictional processes have been suggested to explain the tremor origin (e.g., Iverson et al. 2006; Dmitrieva et al. 2013; Bean et al. 2014).

Ideally, the physical models of tremors could help us to use the measured properties of tremor signals to infer parameters of magmatic systems and ongoing processes such as conduit and crack dimensions, pressures and forces, gas fractions, discharge rates, etc. However, such refined interpretations of tremor observations can only be achieved in a very limited number of studies. In addition to uncertainties of tremor source physical models, one of the main obstacles is the complexity of tremor signals. Indeed, those are often composed of the contribution from multiple sources potentially activated simultaneously within volcano plumbing systems and they can be contaminated by other types of signals such as earthquakes and environmental or anthropogenic noises. In most of the cases, seismo-volcanic tremor as a signal cannot be simply and clearly defined and associated with a particular process within volcanoes. Interpretation of tremors strongly depends on the type of volcano and its activity, and often on the

location of seismometers used for their observations. Because of this complexity, the cases when tremors could be successfully interpreted cannot be simply generalized or applied to different volcanic systems.

Despite of the mentioned difficulties with their interpretation, seismo-volcanic tremors are actively used as empirical indicators of volcanic activity by most of volcano monitoring observatories. In many cases, the recording of sustained tremor is one of the main manifestation of ongoing eruption (e.g. Battaglia et al. 2005a; Senyukov et al. 2015; Battaglia et al. 2016; Duputel et al. 2021). Also, there have been attempts to use tremor amplitudes to empirically estimate lava outputs and eruption sizes as well as fountain and plume heights (e.g., McNutt and Nishimura 2008; Battaglia et al. 2005b; Ichihara 2016; Fee et al. 2017). Additionally, changes of eruptive and, more generally, volcanic activity can be tracked based on variations of tremor properties. In practical terms, this often implies that a volcano observatory establishes some kind of more refined classification with different types of tremors possibly reflecting different eruptive processes. A more advanced approach is to develop automatic classification schemes based on Machine Learning (ML) (e.g., Unglert and Jellinek 2017; Soubestre et al. 2018; Titos et al. 2019).

Following the general tendency of the rapid development of observational and information technologies, the capacities of seismo-volcanic monitoring are constantly evolving. More and more volcanoes are now instrumented with networks of modern digital seismographs. The data are recorded continuously and many observatories make them openly available, often in real time. Also, the computational resources available at volcano observatories become more powerful. These developments provide us with new possibilities to better detect, analyze, and interpret different types of seismo-volcanic signals, including tremors. Comprehensive analysis of the newly available large volumes and flows of monitoring data also poses a significant challenge that requires developing new data processing methods. To be successfully applied in the modern volcano monitoring, these methods should be able to

efficiently analyze data from seismic networks of arbitrary dimensions and geometries, and be easily transportable between different volcanic settings.

With this in mind, the goal of the present chapter is not to provide an exhaustive review of all previously published methods and research results concerning volcanic tremors, but to describe a framework for network-based analysis of tremors. In Sect. 2, we describe the content and properties of seismo-volcanic signals. Section 3 presents a brief reminder of the main single-station approaches for characterizing volcanic tremors. Section 4 shows how the amplitude of tremor recorded across a seismic network can be used to locate its source position. In Sect. 5, we discuss how tremors and their travel times emerge when analysing inter-station covariances (cross-correlations). Section 6 presents a method based on the network covariance matrix. In Sect. 7, we show two examples of the analysis and interpretation of volcanic tremors based on the covariance matrix method. Finally, in Sect. 8, we discuss possible future directions to improve the network-based analysis of volcanic tremors.

2 Seismograms Recorded in the Vicinity of Volcanoes

A seismograph installed in the vicinity of a volcano records all types of seismic signals existing elsewhere and, in addition to this, the waves generated by seismo-volcanic sources. Therefore, the recorded signal (displacement u) can be written as:

$$u = u^{amb} + u^{ant} + u^{tect} + u^{volc} + u^{inst} \quad (1)$$

where u^{amb} and u^{ant} are the natural and the anthropogenic components of the ambient noise wavefield, respectively, u^{tect} are signals generated by tectonic sources not related to the volcanomagmatic activity, u^{volc} is the wavefield generated by different types of seismo-volcanic sources, and u^{inst} is the instrumental noise. Thus, the first step in seismo-volcanic analyses is the “detection” aimed at separating the “useful” part u^{volc} from other contributions (ambient, tectonic, instrumen-

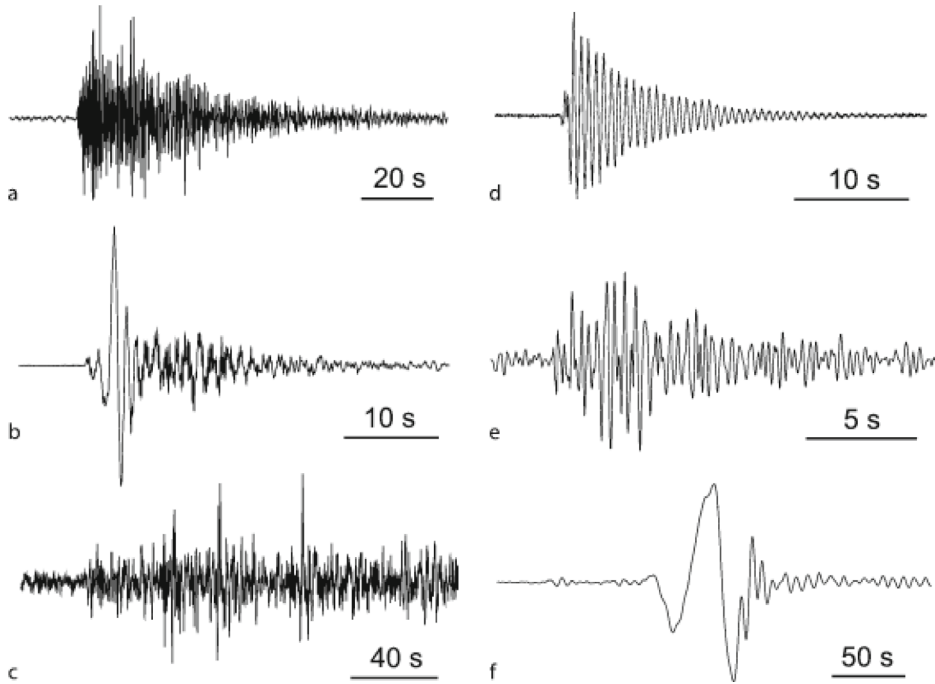


Fig. 1 Example of a classification of seismo-volcanic signals. Reproduced from Kumagai (2009). **a** Volcano-tectonic earthquake that occurred between Miyakejima and Kozujima, Japan; **b** Explosion earthquake observed at Asama volcano, Japan; **c** Tremor that occurred beneath

Mt. Fuji, Japan; **d** Long-period event observed at Kusatsu-Shirane volcano, Japan; **e** Long-period event observed at Guagua Pichincha volcano, Ecuador; **f** Very-long-period event that occurred beneath Miyakejima, Japan (low-pass filtered at 20 s)

tal). This is not a fully trivial task because different terms in Eq. (1) can be active simultaneously and overlap in frequencies.

Nevertheless, the most important goal of volcano-seismological analysis is to interpret u^{volc} in order to infer information about the state of the volcano and processes occurring in the volcano-plumbing system. Seismo-volcanic signals are well known to be very variable in terms of time signature and frequency content (e.g., Kumagai 2009; Chouet and Matoza 2013). This gives rise to multiple classification schemes (see example in Fig. 1), with most frequently used categories are: volcano-tectonic (VT) earthquakes, long-period (LP) events (alternatively called as low-frequency (LF) events), tremors, very-long-period (VLP) events, hybrid events, explosions, and rockfalls. Different classes of signals are, then, related to different types of seismogenic sources and volcano-magmatic processes that are responsible for their excitation.

This detection-classification-interpretation approach is dominant in volcano seismology and figures similar to Fig. 1 can be found in many textbooks, review papers, and websites. Catalogs of classified seismo-volcanic events were initially created “manually” by the staff of volcano observatories. Since a few decades, a significant effort has been done in developing automated algorithms for the detection-classification, with many promising results obtained with ML approaches (e.g., Maggi et al. 2017; Cortés et al. 2021).

An implicit idea of classifications such as the one represented in Fig. 1 is that the seismograms can be divided in reasonably short windows dominated by one type of signal/source and, therefore, corresponding to a particular type of process occurring in volcanoes. An obvious simplification of this approach is the assumption of a single source/process acting at a given time. This assumption might be reasonable for impulsive signals such as earthquakes excited by short-duration processes, i.e., brittle failure for VT earthquakes

or short-living crack resonance for LP events (e.g., Chouet 1996). Consequently, the classifications (both manual and automatic) work rather well for impulsive seismo-volcanic events. However, even for short impulsive signals, classes of “mixed” events such as hybrid events likely reflecting both brittle and fluid processes (e.g., Lahr et al. 1994) are often introduced.

The classification is much more problematic with seismo-volcanic tremors. So far, depending on its variability in time, tremor can be either continuous or intermittent. The latter can be classified as spasmodic (e.g., Ryall and Ryall 1983) or banded (e.g. Fujita 2008; Cannata et al. 2010). The spectral content of tremors is also very variable, with reported frequencies going from less than 1 Hz to more than 20 Hz. Additionally, tremors can be either relatively wide-band or harmonic with very narrow spectral lines. Simultaneous occurrence of different types of tremors generated by different sources are often observed (e.g., Soubestre et al. 2021; Journeau et al. 2022). Moreover, tremors can be accompanied by impulsive volcanic earthquakes. This creates a very strong diversity of tremor signals that cannot be classified into a single category as it could be suggested by Fig. 1. Classifying volcanic tremors into a few simple categories does not work either.

An important property of volcanic tremors is that they typically have durations much longer than a few tens of seconds and, therefore, reflect relatively slow evolutions of volcano-magmatic systems at time scales from hours to months. Two examples of long-duration tremors are shown in Fig. 2. The first one has been recorded during the July-August 2017 eruption (from 2017-07-13 to 2017-08-27) of Piton de la Fournaise volcano at La Réunion island. This was a typical flank (rift-zone) eruption (Dumont et al. 2021) of this basaltic hot-spot volcano with a rather long duration (46 days). We show in Fig. 2a and b two-day-long records corresponding to its beginning and terminal phases, respectively. We can clearly see that the tremor signal does not remain stationary during the eruption, which was preceded by a swarm of volcano-tectonic earthquakes (Fig. 2c). The tremor amplitude is not constant and, in particular, it increases at the eruption onset (Fig. 2d)

and then decreases shortly after it (Fig. 2a). The tremor is continuous at the beginning of the eruption (Fig. 2e), while it becomes strongly intermittent at the end of the eruption when it appears as a sequence of very closely occurring LP events (Fig. 2f) (Journeau et al. 2023).

The second example (Fig. 2g) shows two days of continuous seismic signal recorded in the vicinity of Klyuchevskoy volcano in Kamchatka, Russia, in mid-March 2016. This volcano is known for its both co- and inter-eruptive long-duration tremors (Gordeev et al. 1990; Droznin et al. 2015; Soubestre et al. 2018, 2019). The considered two-day period corresponds to a preparatory phase of an eruption that started on April 6, 2016. During this period, both shallow and deep tremor sources were active (Journeau et al. 2022). The resulting tremor is very non-stationary. Also, continuous records in the very active Kamchatka subduction zone contain many signals from regional tectonic earthquakes (Fig. 2h).

In conclusion, the volcanic tremors cannot be classified as a simple category (or a set of simple categories) of signals. Instead, they should be considered as long-duration episodes of sustained and often non-stationary seismo-volcanic activity. The non-stationarity of volcanic tremors reflects the non-stationarity of physical processes occurring in volcanic systems, that are schematically illustrated in Fig. 3. Magmatic feeding systems beneath volcanoes extend over large range of depths down to the upper mantle (e.g., Cashman et al. 2017), with magma storages present at different levels. During the volcanic crises (including eruptions and their preparation phases), these systems are destabilized at different levels. As a result, multiple processes such as magma and fluid pressure transport, degassing, and fracturing are activated nearly simultaneously and often at different locations within the system. Interplay between these processes gives rise to sometimes very complex scenarios that are reflected in the complexity of the observed seismo-volcanic tremors.

In a most general case, a time (t) dependent distribution displacement $u_i^{volc}(\mathbf{r}_r, t)$ associated with seismo-volcanic sources recorded on the component i of a receiver located in $\mathbf{r}_r$ (the subscript r

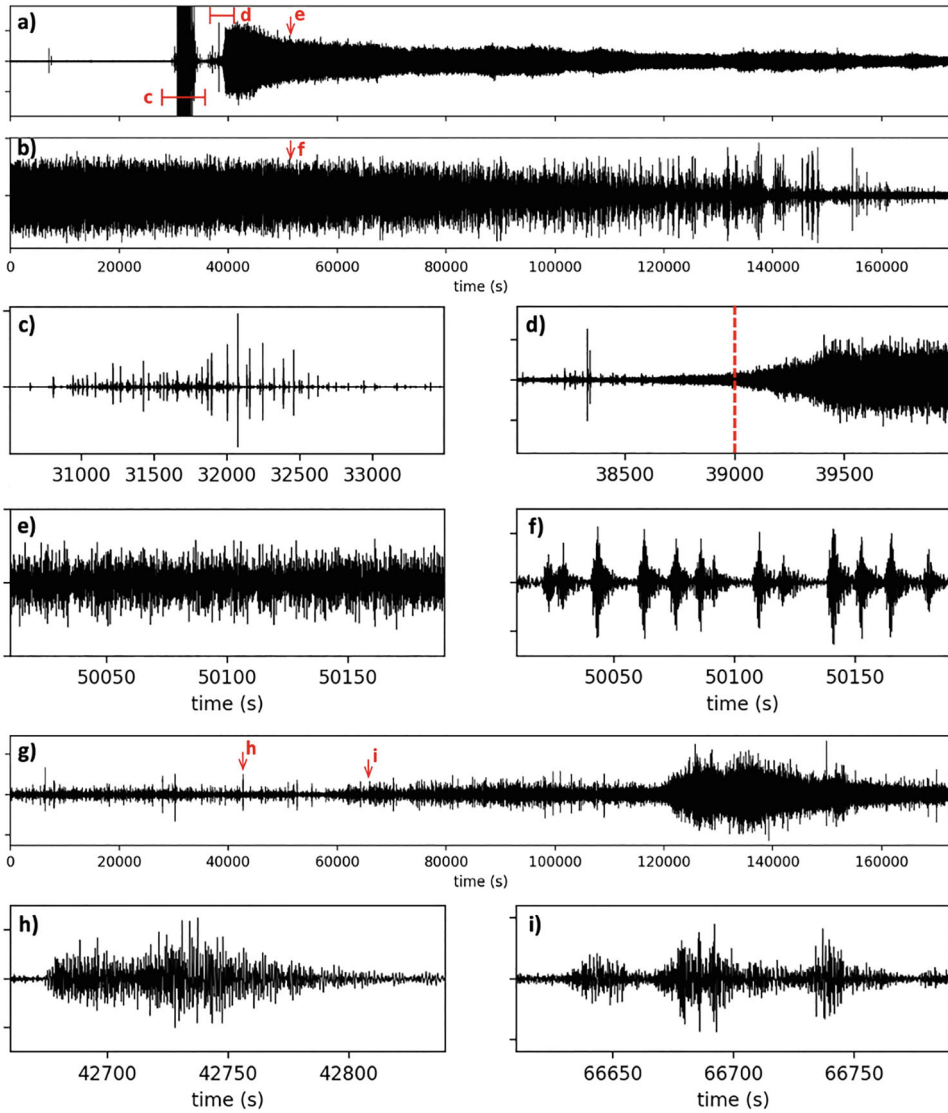
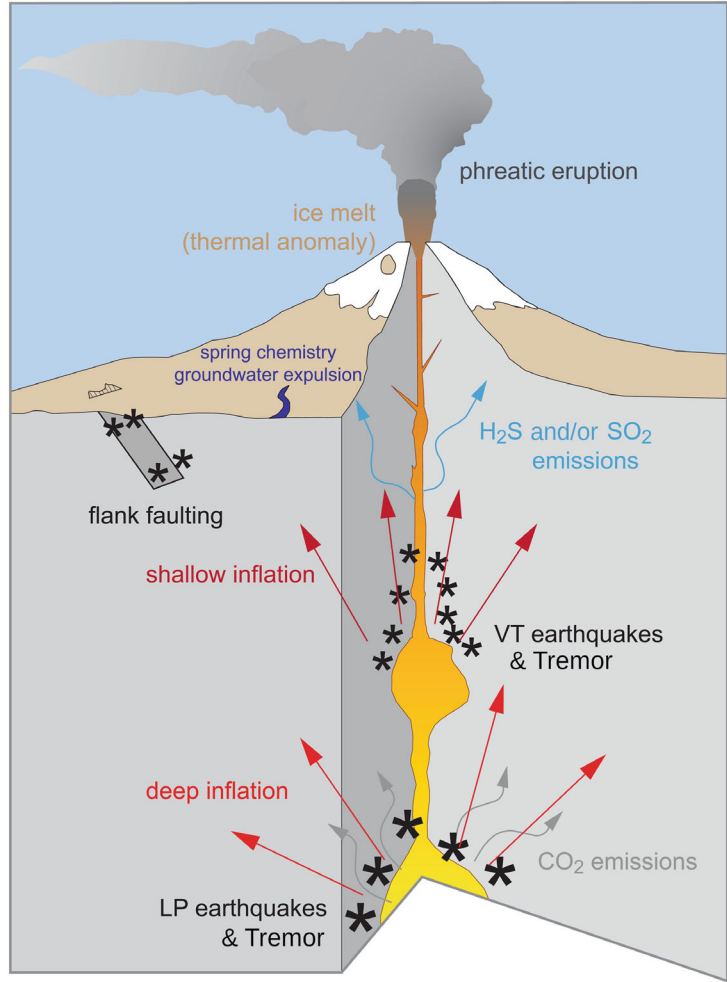


Fig. 2 Examples of seismograms recorded on volcanoes. Normalized vertical component velocities band-passed between 0.5 and 25 Hz are shown. **a** and **b** Two-day-long seismograms containing long-duration tremors emitted during the July–August 2017 eruption (from 2017-07-13 to 2017-08-27) of Piton de la Fournaise volcano (PdF) recorded by station RVL (Piton de la Fournaise Volcano Observatory Network, doi:10.18715/REUNION.PF) located ~1 km south-west of the main crater. **a** Beginning of the eruption (seismogram starting time: 2017-07-13 10:00 UTC). **b** Terminal phase of the eruption (seismogram starting time: 2017-08-26 00:00 UTC). **c–f** Zoomed view on portions of signals indicated with red letters in (**a**)–(**b**). **c** Swarm of volcano-tectonic earthquakes preceding the

July–August 2017 PdF eruption. **d** Emergence of eruptive tremor associated with the onset of the eruption indicated with a red vertical dashed line. **e** 180 s of continuous tremor during the initial phase of the eruption. **f** 180 s of intermittent tremor during the terminal phase of the eruption. **g** Two-day-long seismogram recorded in mid-March 2016 by station SV13 (temporary experiment KISS, Shapiro et al. (2017b), doi: 10.14470/K47560642124) located ~4.5 km north of the main crater of Klyuchevskoy volcano in Kamchatka, Russia (seismogram starting time: 2016-03-14 10:00 UTC). **h–i** Zoomed view on portions of signals indicated with red letters in (**g**). **h** Regional subduction-zone earthquake in Kamchatka. **i** 180 s of intermittent tremor associated with the Klyuchevskoy activity

Fig. 3 Idealized representation of a generic stratovolcano showing various types of volcanic processes and possible associated seismo-volcanic sources.

Modified from Poland and Anderson (2020)



stands for receiver) can be written as (Kumagai 2009):

$$u_i^{volc}(\mathbf{r}_r, t) = \int_{-\infty}^{+\infty} \iiint_V f_j^{volc}(\mathbf{r}, \tau) G_{i,j}(\mathbf{r}_r, t - \tau, \mathbf{r}, 0) dV(\mathbf{r}) d\tau \quad (2)$$

where $f_j^{volc}(\mathbf{r}, \tau)$ is a time and space dependent equivalent body force (j -component) and $G_{i,j}(\mathbf{r}_r, t - \tau, \mathbf{r}, 0)$ is the Green's function, i.e., the mathematical representation of the seismic wave propagation from the source to the station. For volcanic earthquakes, the force distribution can be considered as a point source located in $\mathbf{r}_s$ (the subscript s stands for source) corresponding either to a single force or to a seismic moment tensor (Kumagai 2009). In this case, and consid-

ering an elastic approximation for seismic waves, the recorded displacement can be schematically represented by a time convolution:

$$u_i^{volc}(\mathbf{r}_r, t) = \int_{\tau_s}^{\tau_s + \delta\tau} S^{volc}(\mathbf{r}_s, \tau) \tilde{G}(\mathbf{r}_r, t - \tau, \mathbf{r}_s, 0) d\tau \quad (3)$$

where τ_s and $\delta\tau$ are the event starting time and duration, respectively, $S^{volc}(\mathbf{r}_s, \tau)$ is a generic representation of a source time function that can be either a force vector or a moment tensor, and $\tilde{G}(\mathbf{r}_r, t - \tau, \mathbf{r}_s, 0)$ represents either the Green's function or its spatial derivative.

Equation (3) is not applicable in the case of seismo-volcanic tremors for two reasons. First, the tremor source time functions are not localized in a short interval $\delta\tau$ but rather have long dura-

tions and often complex variability in time. Second, as discussed above, many records of seismic tremors contain signatures of different sources acting simultaneously. Therefore, the most general case of seismic tremor should be described with a full Eq. (2). In the case of a few tremor sources remaining stationary in space within the considered time window, it can be simplified as:

$$u^{volc}(\mathbf{r}_r, t) = \sum_k \int_{-\infty}^{+\infty} S^k(\mathbf{r}_s^k, \tau) \tilde{G}(\mathbf{r}_r, t - \tau, \mathbf{r}_s^k, 0) d\tau \quad (4)$$

where k indexes different acting tremor sources located in positions $\mathbf{r}_s^k$.

Within the framework introduced above, an ideal goal of the analysis of seismic tremors could be formulated as retrieving the full source time function $f_j^{volc}(\mathbf{r}, \tau)$ appearing in Eq. (2). This is, however, not feasible because of the limited number of recording stations, the contamination by non-volcanic signals, and the poorly known subsurface structure (the Green's functions). Therefore, the tremor analysis can be more reasonably formulated based on Eq. (4). In this case, the first goal of the analysis is to identify the principal tremor sources active during the considered period of volcanic activity. This should be followed by characterizing the source time functions $S^k(\mathbf{r}_s^k, \tau)$. Their exact retrieval is again not feasible. However, with appropriate data coverage, an approximate characterisation of slow varying properties (location in space and frequency content) can be obtained, as we will discuss in the following sections.

3 Single Station Analysis

Despite the rapid development of networks of instruments on many volcanoes in the World, methods based on a single station remain very important for volcano monitoring at volcano observatories with limited resources, because of the simplicity of their implementation and their robustness.

3.1 Tremor Amplitudes at a Single Station

The simplest approach for characterizing seismo-volcanic signals consists of computing the average signal amplitude in a moving window (typically a few minutes long) on a single component of a single station. The most used method is called Real-time Seismic Amplitude Measurement (RSAM) (Endo and Murray 1991) and its variants are implemented in most of volcano observatories. This approach has the advantage of simplicity. It does not require a dense network of instrumentation and can be implemented even with old-type analogous seismic recorders. As a consequence, the single-station average amplitude estimation is very robust.

Despite its simplicity, the RSAM method gives a very useful overall view of the seismo-volcanic activity and, in particular, of volcanic tremors. It is often used as the main indicator (in the absence of visual observation) of the beginning and the end of an eruption. This is illustrated in Fig. 4 that shows the RSAM computed during the June 2019 eruption of the Piton de Fournaise volcano at La Réunion Island. This relatively short eruption started at 02:35 UTC on June 11, 2019 as very clearly seen in the RSAM plot and remained active approximately till 08:00 UTC on June 13.

Also, there have been a few attempts to establish a scaling between the tremor amplitude and the eruption size (McNutt 1994), based on measuring the reduced displacement (Aki and Koyanagi 1981) that represents a maximal tremor amplitude corrected for geometric spreading (amplitude times distance) and instrument gain. The tremor reduced displacement has been reported to roughly scale with both the ash column height and the volcanic explosivity index (VEI) (Newhall and Self 1982), as well as with the square root of the cross sectional area of the eruptive vent. A recent study confirms the existence of a relationship between tremor amplitudes and eruption plume height as well as eruption duration (Mori et al. 2022). On the other hand, this relationship between tremor amplitude and plume height is not applicable for all volcanoes, as for example during the 2010 Eyjafjallajökull eruption (Iceland)

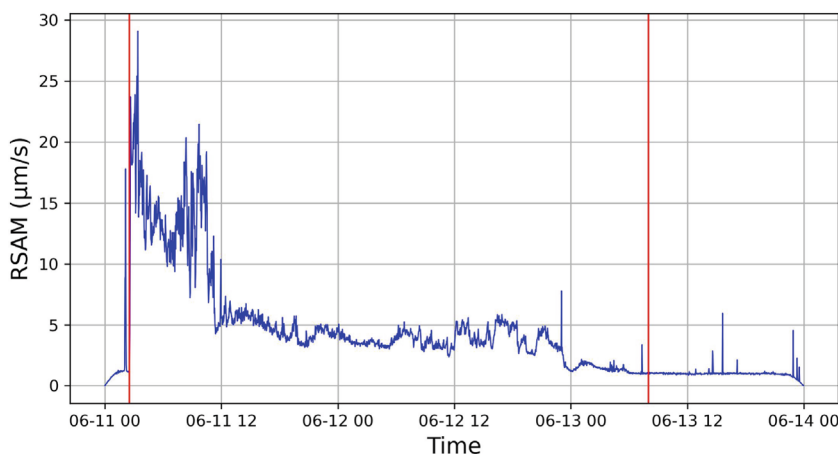


Fig. 4 Example of RSAM computed from a co-eruptive tremor. RSAM evolution computed between 2019-06-11 00:00 and 2019-06-14 00:00 UTC at seismic station DSO (Piton de la Fournaise Volcano Observatory Network, doi:

10.18715/REUNION.PF), using vertical component and filtering between 0.5 and 10 Hz. The two vertical red lines indicate the beginning and the end of the eruption, respectively

when a drop in seismic tremor was observed while the plume height increased (Gudmundsson et al. 2010), or energetic banded tremor was not coinciding with elevated plume height (Caudron et al. 2022). Similarly, the relationship between seismic tremor amplitude and eruptive duration is not always verified. The recent 2021 Fagradalsfjall eruption (Iceland) was characterized by a seismic tremor whose amplitude did not correlate with the eruptive lava fountain episode duration, but with the duration of the repose time between those eruptive episodes (Eibl et al. 2023; Soubestre et al. 2025).

Moreover, power law scaling between tremor amplitudes and magma discharge rate have been proposed with different power indices based on various data sets reviewed by Ichihara (2016). However, this kind of scaling remains empirical and might lead to erroneous estimations when applied without identifying the tremor origin (e.g., shallow vs. deep), or if more than one tremor source is active at the same time (Eibl et al. 2017a).

While being very useful for the real-time monitoring, the measurement of tremor amplitudes at a single station is not sufficient to analyze the complexity of tremor and to separate possible different sources (Eq. 4). Therefore, other signal properties such as spectral content and polarization should be used for a more advanced analysis, as detailed in the following sections.

3.2 Spectral Content of Tremor at a Single Station

Different types of volcanic tremors have distinct spectral properties. While some of them are rather broadband, others have spectra consisting of one or several sharp peaks (these latter are most likely related with the excitation mechanisms involving internal resonances in the plumbing systems). Therefore, the spectral analysis is a very powerful tool for distinguishing different tremor types and their sources. As discussed in Sect. 2, the properties of seismo-volcanic tremors vary in time following the changes occurring within the plumbing systems. Therefore, these changes are reflected by variations of the tremor spectral content in time and can be tracked by applying a time-frequency analysis.

A spectrogram of two days of seismic tremors recorded near the Klyuchevskoy volcano (Kamchatka, Russia) is shown in Fig. 5. It clearly demonstrates that, in addition to variations of tremor amplitudes, its spectral characteristics are changing over time. During the initial 60,000 s (16.7 h) of this record, the tremor is dominated by relatively low frequencies with a few clearly distinguishable spectral lines. Several impulsive events on top of this tremor are observed and most likely correspond to tectonic earthquakes

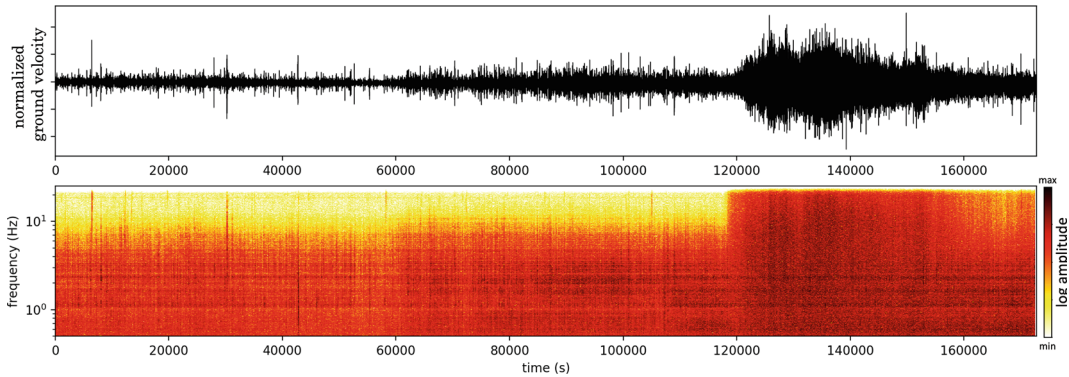


Fig. 5 Example of a tremor spectrogram. Upper frame shows a two-day-long tremor record at the Klyuchevskoy volcano in Kamchatka, Russia (same as Fig. 2g, seismo-

gram starting time: 2016-03-14 10:00 UTC), whose spectrogram is shown below (bandpassed between 0.5 and 5 Hz)

(Fig. 2h). Then, between 60,000 and 120,000 s (16.7 and 33.3 h), the amplitude of the tremor slightly increases while its spectral characteristics do not change significantly. This might indicate that during this period of volcanic activity, the tremor was generated by the same source and process with slightly increasing intensity after the first 16.7 h (60,000 s). Conversely, after 120,000 s (33.3 h), the strong increase of the tremor amplitude is also accompanied by a significant variation of its spectral properties, with appearance of high-frequency (>10 Hz) energy and more significant time intermittence seen as vertical bands on the spectrogram. These changes likely indicate that the tremor origin has been modified after the initial 33.3 h (120,000 s) of the record. The fact that low-frequency (between 1 and 3 Hz) spectral lines are still observed might indicate that the generating mechanism that has been acting during the first 33.3 h still persists and that an additional source/process generating higher frequency tremor is activated.

While the time-frequency analysis is a very efficient tool for detecting changes in the composition of the signal recorded at a single component that might be caused by variations of the tremor generating mechanism, its interpretation is rather ambiguous. One important reason for this ambiguity is that the location of the tremor source cannot be inferred from the one-component signal. A second reason is that the source and the propagation effects are not easy to separate based only on sin-

gle station records. So far, the low-frequency spectral lines seen in Fig. 5 could be attributed either to sources properties, or to interaction of seismic waves with the near-station structure, i.e., the so-called site effect (e.g., Fehler 1983; Goldstein and Chouet 1994; Konstantinou and Schlindwein 2002), or to the scattering on structural heterogeneities in the propagation medium (Barajas et al. 2023).

3.3 Polarization of Tremor Signal at a Single Station

If a tremor generating seismic source remains at the same location and with a constant mechanism, the emitted seismic waves will be characterized by a constant (even possibly complex) polarization. This polarization expresses itself as a particular correlation between ground motions recorded at different components of a single station (one vertical and two horizontals). Therefore, it can be analyzed when records with three-component stations are available.

A simple approach to detect a persistent polarization in continuous signals is to analyze the single-station inter-component cross-correlation function of one pair of components (EN, EZ or NZ). For a seismic noise generated by randomly distributed sources, these cross-correlations computed over relatively short time windows are random and variable in time. On the contrary, for

a signal generated by a persistent tremor source they remain stable in time. This stability of the inter-component cross-correlation function can be characterized by comparing results from consecutive time windows resulting in an efficient tremor detector (Journeau et al. 2020, 2022). Additionally, the waveform of the cross-correlation function can be used as a “fingerprint” of a particular tremor source (Droznin et al. 2015) and helps to separate different tremor generating processes.

A more advanced polarization analysis is performed with using the full set of inter-component cross-correlations (cross-spectra) at a single station, that forms a 3x3 covariance matrix (Vidale 1986). This matrix is complex and Hermitian and its three eigenvalues are real, while eigenvectors are complex. The ratio between eigenvalues can be used to determine the degree of polarization. When a single eigenvalue is much larger than the two remaining ones, a single wave is dominating the signal. When no dominating eigenvalue is observed (the three eigenvalues are of the same order of magnitude), the signal represents a mixture of different types of waves. For a dominating wave, the respective eigenvector can be analyzed in the framework of the “complex polarization analysis” (e.g., Vidale 1986; Levshin et al. 1989) in order to determine the type of polarization (linear vs elliptical) and to measure parameters such as the backazimuth and the incident angle of the polarization vector. Polarization analysis has been applied to volcanic tremors in the time (e.g., Konstantinou and Schlindwein 2002; Ereditato and Luongo 1994), frequency (e.g., Chouet et al. 1997), and time-frequency (e.g., Haney et al. 2020) domains. The latter approach is more selective and better separates different signals. Thus, Haney et al. (2020) studied the seismic tremor recorded during eruptive activity over the course of the 2016–2017 eruption of Bogoslof volcano, Alaska, with applying the time-frequency polarization analysis to three-component seismic data and found that it was dominated by P-waves. This information helped the authors to improve estimates of average reduced displacement.

3.4 Identifying Different Types of Volcanic Tremors with Machine Learning at a Single Station

The methods described in the previous paragraphs can be very efficiently applied to continuous seismic records to estimate tremors amplitudes, spectral characteristics, and polarization properties. Based on these measurements, it is possible to identify different types of tremors, possibly corresponding to different processes/locations within the volcano plumbing system. For a relatively short tremor episode, this kind of inferences can be done with a visual inspection of the analysis results. However, in most cases when tremor remains for several days or months, the amount of information to account for becomes too large and its unbiased analysis requires more formal and automated approaches. As in many other disciplines, ML approaches are becoming very popular in volcano seismology for automatic classification of signals and pattern recognition (e.g., Titos et al. 2019; Cortés et al. 2021).

Supervised “classification” of volcanic tremors would consist in training algorithms like neural networks, random forest, support vector machines, or others, based on “labeled” waveforms of different types of tremors. In other words, this approach requires an a priori information about possible properties of tremor signals. As explained in Sect. 2, the a priori classification of tremor signals is rather problematic because of the huge variability of possible combinations of many types of tremors.

Therefore, unsupervised methods are better adapted for the analysis of continuous seismo-volcanic tremors. In most cases, this implies applying various “clustering” algorithms to group tremor signals based on their distinct amplitudes and spectral characteristics (and eventually polarization properties). Unglert et al. (2016); Unglert and Jellinek (2017) have demonstrated that clustering algorithms existing in modern ML toolboxes (such as Principal Component Analysis, Hierarchical Clustering, Self Organized Maps) applied to single station data can efficiently detect volcanic tremors or other types of seismo-volcanic signals (such as earthquakes and lahars) and

identify their types. Hence, unsupervised volcanic tremor classifiers are generally using single-station based signal features, such as RSAM time series (Steinke et al. 2023), spectra (Unglert et al. 2016; Unglert and Jellinek 2017) or single-station inter-component cross-correlation functions (Yates et al. 2023; Makus et al. 2023). Such ability to rapidly group tremors without prior knowledge about the character of the seismicity at a given volcanic system holds great potential for real time or near-real time applications, and thus ultimately for eruption forecasting. More recently, Steinmann et al. (2024) showed that scattering transform-based features from single-station continuous seismograms, combined with Uniform Manifold Approximation and Projection (UMAP), can uncover the continuous evolution of volcanic tremor characteristics, revealing dynamic changes in the underlying magmatic system. At the same time, interpreting the origin of the observed groups of tremors based on results from a single station remains problematic because of the unknown location of their sources and the difficulty in separating source and propagation effects.

4 Amplitude-Based Network Analysis of Seismo-Volcanic Tremors

As mentioned in the previous section, one of the main shortcomings of single station methods is their impossibility to determine the location of the tremor source. This location can be found based on simultaneous analysis of records at several seismic stations, or, in other words, of a seismic network. A set of methods is based on measuring the tremor amplitudes at different stations and finding the source position that better predict the decay of these amplitudes with propagation distance.

The *Amplitude Source Location (ASL)* method was developed by Battaglia and Aki (2003) for a configuration when a single localized and fixed tremor source dominates the recorded wavefield. The amplitude at station i is given by:

$$A_i = \frac{A_0}{\gamma_i d_i^\alpha} \exp \left(-\pi f \int_{path_i} \frac{dl}{Qv} \right) \quad (5)$$

where A_0 is the source amplitude, the term $1/(d_i^\alpha)$ represents the geometrical spreading with $\alpha = 1$ for body waves or $\alpha = 1/2$ for surface waves, γ_i is the amplitude correction at station i to take site effect into account, d_i is the distance from the source to station i , f is the frequency, and v , Q and dl are respectively the wave velocity, the attenuation quality factor and the incremental distance along the path from the source to the station. The attenuation quality factor Q is often estimated based on seismic coda amplification factors (Aki and Ferrazzini 2000) measured from regional or local earthquakes. Note that for uniform velocity and attenuation, parameters v and Q are constant and $\gamma_i = 1$ (no site effect) so that Eq. (5) simplifies as:

$$A_i = \frac{A_0}{d_i^\alpha} \exp \left(\frac{-\pi f d_i}{Qv} \right) \quad (6)$$

The tremor source is finally located at the position of a 3-D grid minimizing the misfit between calculated and observed amplitudes across the network (Gottschämmer and Surono 2000). The method is often used in the 5–10 Hz frequency range in which, likely due to scattering phenomena, the assumption of isotropic radiation is valid and Eq. (6) can be used. Recent improvements of this method include the consideration of depth-dependant scattering and attenuation at Nevado del Ruiz volcano (Kumagai et al. 2019), and relative locations at Meakandake volcano (Ogiso and Yomogida 2021).

Volcanic tremor was located with the ASL method at many different volcanoes. The first use of this method on volcanic tremor was carried out at Piton de la Fournaise, where the tracking of shallow tremor sources appeared to be an efficient tool to monitor the opening of new eruptive fissures during the 1998 and 1999 eruptions (Battaglia and Aki 2003; Battaglia et al. 2005a). At Mount Etna, shallow tremor sources were located close to eruptive craters during pre-effusive and effusive phases of the 2004 eruption (Di Grazia et al. 2006), as well as beneath the South East Crater imaging shallow conduits where magma degassing was

taking place during strombolian activity and fire fountain episodes in 2007 (Patanè et al. 2008). Still at Etna, tremor was located 1–2 km a.s.l. below the North East Crater where a magma body was cyclically feeding some fire fountains in 2011, during which the tremor source was migrating shallower towards the North South East Crater (Cannata et al. 2013; Moschella et al. 2018). Tremor-like signals generated by lahars and pyroclastic flows were tracked descending on the flanks of Cotopaxi (Kumagai et al. 2009) and Tungurahua (Kumagai et al. 2010). Shallow tremor sources were located in the old north crater, in the lava lake of the active crater and in an intermediate fumaroles field of the Erta’ Ale caldera during an experiment in 2003 (Jones et al. 2012). Shallow migrations of tremor sources were observed prior to phreatic eruptions of Japanese volcanoes, with lateral migrations in 2008 at Maekandake (Ogiso and Yomogida 2012) and descending migration (over ~2 km) in 2014 at Ontake (Ogiso et al. 2015).

An alternative to the ASL method is the *Seismic Amplitude Ratio* method. It is based on the ratio of seismic amplitude at pairs of stations i and j . For uniform velocity and attenuation, using Eq. (6) it comes:

$$R_{i,j} = \frac{A_i}{A_j} = \left(\frac{d_j}{d_i}\right)^\alpha \exp\left(\frac{-\pi f}{Qv}(d_i - d_j)\right) \quad (7)$$

The ratio $R_{i,j}$ is calculated for the different station pairs of the network and the misfit between calculated and observed ratios is minimized to find the 3-D position of the tremor source.

The first application of this method was carried out by Carbone et al. (2008) to locate tremor at Etna during the December 2005 to January 2006 non-eruptive period. The tremor source was positioned in a volume with a centroid located at 0.6 km above the sea level (~2.2 km below the surface), a maximum length and width of about 2 and 1 km, respectively, and slightly shifted to the south of the Summit Craters. Later, the seismic amplitude ratio method was used to image the dynamics of dyke propagation in real time during the January 2010 Piton de la Fournaise eruption (Taisne et al. 2011). In Kamchatka, migrations of tremor sources were interpreted as magma

movements prior to the 2012-13 Tolbachik eruption (Caudron et al. 2015). In Iceland, the amplitude ratio method was combined with both array-based azimuth determination and 3-D seismic full wavefield elastic numerical modelling to constrain a migrating pre-eruptive tremor location to the uppermost 2 km of the crust above the propagating dyke at Bardarbunga in 2014 (Eibl et al. 2017b). This pre-eruptive tremor was attributed to swarms of microseismic events associated with fracturing during the dyke formation, with seismically silent subsequent magma flow in the newly formed dyke. An exception occurred on September 3, 2014, when the tremor was located beneath ice cauldrons located 12 km south of the ongoing eruptive site, as confirmed later by another study (Caudron et al. 2018). In Japan, tremor sources associated with phreatomagmatic activity at Aso volcano from December 2013 to January 2014 were found to be located in a cylindrical region of the top 400 m below the surface, interpreted as a network of fractures (Ichimura et al. 2018). Still in Japan, tremor sources were located at 0.5-1 km depth and 1 km north from Motoshirane cone ~2 min before the 2018 phreatic eruption of Kusatsu-Shirane, possibly reflecting small shear fractures induced by sudden hydrothermal fluid injection into an impermeable cap-rock layer which triggered the eruption (Yamada et al. 2021). In New Zealand, tremor migration associated with phreatic activity was observed at Whakaari/White Island volcano (Caudron et al. 2021). In the Galápagos Islands, the sources of both pre- and co-eruptive tremor were located with the seismic amplitude ratio method during the 26 June 2018 eruption at Sierra Negra (Li et al. 2022). The pre-eruptive tremor was interpreted as generated by fracturing associated with dyke propagation, opening pathway later used for silent magma flow as already suggested at Bardarbunga (Eibl et al. 2017b). The different spectral content of co-eruptive tremor compared to pre-eruptive tremor allowed for a precise timing of the eruption onset.

5 Tremor and Inter-Station Cross-Correlations

Tremor amplitudes analyzed in the previous section to locate their sources contain only a small portion of the information. At the same time, the phase of tremor signals seems to be difficult to analyze because of its random nature. Indeed, according to Eq. (4), this phase is randomized by the source processes $S^k(\mathbf{r}_s^k, \tau)$. However, the randomness of the source time function can be compensated by computing cross-correlations between station pairs. To demonstrate this, let us consider a simplified case when a single tremor source is acting at position $\mathbf{r}_s$ and remains stationary in time. We then re-write Eq. (4) in the Fourier spectral domain as:

$$U^{tr}(\mathbf{r}_r, \omega) = S(\omega) \tilde{G}(\mathbf{r}_r, \mathbf{r}_s, \omega) \quad (8)$$

where $U^{tr}(\mathbf{r}_r, \omega)$ is the Fourier spectrum of the tremor signal recorded at position $\mathbf{r}_r$, $S(\omega)$ is the Fourier spectrum of the source time function, and $\tilde{G}(\mathbf{r}_r, \mathbf{r}_s, \omega)$ is the generalized Green's function in the Fourier domain.

An equivalent of the time-domain cross-correlation in the Fourier domain is the cross-spectrum, that is computed as the product between one spectrum and the complex conjugate of another. For a cross-spectrum of tremor recorded at two stations 1 and 2 (located in $\mathbf{r}_1$ and $\mathbf{r}_2$, respectively) this gives:

$$CC_{1,2}(\omega) = |S(\omega)|^2 \tilde{G}(\mathbf{r}_1, \mathbf{r}_s, \omega) \tilde{G}^*(\mathbf{r}_2, \mathbf{r}_s, \omega) \quad (9)$$

In Eq. (9), the random source phase disappears and the resulting cross-correlation is formed by two factors. The first one is the power spectral density of the tremor source $|S(\omega)|^2$. The second factor is the cross-correlation of two Green's functions that depends on the wave propagation between the source and the two receivers. If the tremor position and mechanism do not change, this second factor remains constant. As a consequence, the inter-station cross-correlation waveform is very sensitive to modifications of the tremor source spectrum and mechanism, or to a change of its posi-

tion. Therefore, it can be used as a tremor source “fingerprint”.

The Earth's interior is an heterogeneous medium from the wave propagation point of view, and in particular its shallow crust in volcanic regions. In such a medium, it is convenient to consider the seismic wavefield as being composed of two contributions (e.g., Campillo and Margerin 2010). First, “ballistic” waves propagate in a smooth slowly varying medium where the wave fronts can be perfectly tracked and wave travel times defined. The propagation of waves can then be successfully described by geometrical methods such as ray theory. On top of this smooth wavefield, the scattering on small-scale obstacles or lateral variations of elastic parameters result in wave fronts distortion and deflection of seismic energy in all possible directions. As a result, a seismic coda is formed after the arrival of the ballistic waves.

The “ballistic” part of the Green's function can be simplistically described as a simple combination of the wave travel time $t_{r,s}$ between the source s and the receiver r positions, with the amplitude attenuation $a(\mathbf{r}_r, \mathbf{r}_s)$:

$$\tilde{G}^{bal}(\mathbf{r}_r, \mathbf{r}_s, \omega) = a(\mathbf{r}_r, \mathbf{r}_s) e^{-i\omega t_{r,s}} \quad (10)$$

As a result, Eq. (9) can be re-written as:

$$CC_{1,2}(\omega) = |S(\omega)|^2 a(\mathbf{r}_1, \mathbf{r}_s) a(\mathbf{r}_2, \mathbf{r}_s) e^{-i\omega(t_1 - t_2)} + |S(\omega)|^2 CC_{1,2}^{scat}(\omega) \quad (11)$$

The first term in this expression contains information about the relative propagation time from the tremor source to receivers 1 and 2 : $(t_1 - t_2)$ and, therefore, can be used to locate the source position (e.g., Ballmer et al. 2013; Droznin et al. 2015). The second term is more complex and mainly depends on cross-correlations of the scattered waves schematically denoted as $CC_{1,2}^{scat}(\omega)$. Despite its complexity, this term remains constant for a source with fixed position/mechanism and, therefore, makes the cross-correlation “fingerprinting” more selective.

We illustrate the properties of the inter-station tremor cross-correlations with an analysis of records from the monitoring seismic network

operated by the Kamchatkan Branch of the Russian Geophysical Service on the Klyuchevskoy Group of Volcanoes in Kamchatka, Russia (Droznin et al. 2015). This network (Fig. 6a) records tremors generated by several active volcanoes and, therefore, is very convenient for illustrating analysis of multiple tremor sources.

Examples of 1,000 s (16.7 min) long vertical component continuous records from stations LGN and KMN are shown in Fig. 6b and c, respectively. We show records for 3 days: 2010-03-05, when the Klyuchevskoy volcano was erupting; 2011-04-28, when all volcanoes were quiescent; and 2012-12-01, a few days after the beginning of the Tolbachik eruption. All shown records look like “random” noise and their most distinctive feature is the difference in amplitudes.

Figure 6d–f show examples of day-long cross-correlations corresponding to the three previous dates (computed between LGN, highlighted with yellow in Fig. 6a, and all other stations). To minimize the contribution of strong signals such as earthquakes or calibration pulses, we followed the approach of Bensen et al. (2007) to pre-process the continuous records with applying a spectral whitening between 0.1 and 4 Hz followed by a one-bit normalization.

Cross-correlations computed during a day when all surrounding volcanoes were quiet look like random time series (Fig. 6e). The result is very different during the days when Klyuchevskoy (Fig. 6d) or Tolbachik (Fig. 6f) volcanoes were active. During the Klyuchevskoy activity, strong one-sided signals emerge in all cross-correlations. A close inspection shows that this signal propagates from a vicinity of station LGN (closest station to the active crater of the Klyuchevskoy volcano) to all other stations. At some station pairs (e.g., KPT-LGN or CIR-LGN), we can distinguish a relatively low-frequency short arrival that corresponds to ballistic contribution in Eq. (11). Much broader tails containing higher frequencies correspond to “scattering” contributions. During the Tolbachik activity, we see again strong emerging asymmetric signals. However, their shapes and relative travel times are very different from those recorded during the

period of the Klyuchevskoy activity. In particular, for most of the station pairs the maxima were shifted from the left to the right side, implying that the tremor source is located further from LGN than from most other stations.

Equation (9) predicts that if the position and mechanism of the tremor source as well as the medium remain constant, the irregular source time function is cancelled and the resulting cross-correlation at a given station pair remains stable in time. The scenario described above can be realized when the eruptive centre of a volcano remains in the same position during long eruptive episodes. In this case, the cross-correlation waveforms computed from different time windows during these episodes will remain stable in time. This property is illustrated in Fig. 7a and b, that show cross-correlations computed between stations CIR and LGN during 8 consecutive days in January 2010 and in January 2013 when Klyuchevskoy and Tolbachik volcanoes erupted, respectively. During both of the 8-days periods, the cross-correlation waveforms remain very stable in time. In both cases, relatively low-frequency ballistic waves can be seen at ~ -5 s, implying that they first arrive at LGN that is closer to both eruptive centers (tremor sources). At the same time, the “scattered” contribution to the cross-correlation is much stronger during the Tolbachik eruption (Fig. 7b), that is more distant relative to the considered pair of stations. This makes the cross-correlation waveforms corresponding to activities of the two volcanoes very different. The presented examples show that cross-correlations computed between a single station pair are very sensitive to the location of the source. As a result, they can be very efficiently used as “fingerprints” of tremors emitted by particular volcanoes. Alternatively, changes in the cross-correlation waveforms can reflect some changes of the medium/topography caused by volcanic phenomena such as intrusions, growth of eruptive cones, collapses, etc.

The similarity between cross-correlation waveforms can be quantified with computing a Pearson correlation coefficient. Figure 7c and d demonstrate that when selecting as fingerprints cross-correlation waveforms during respective days of

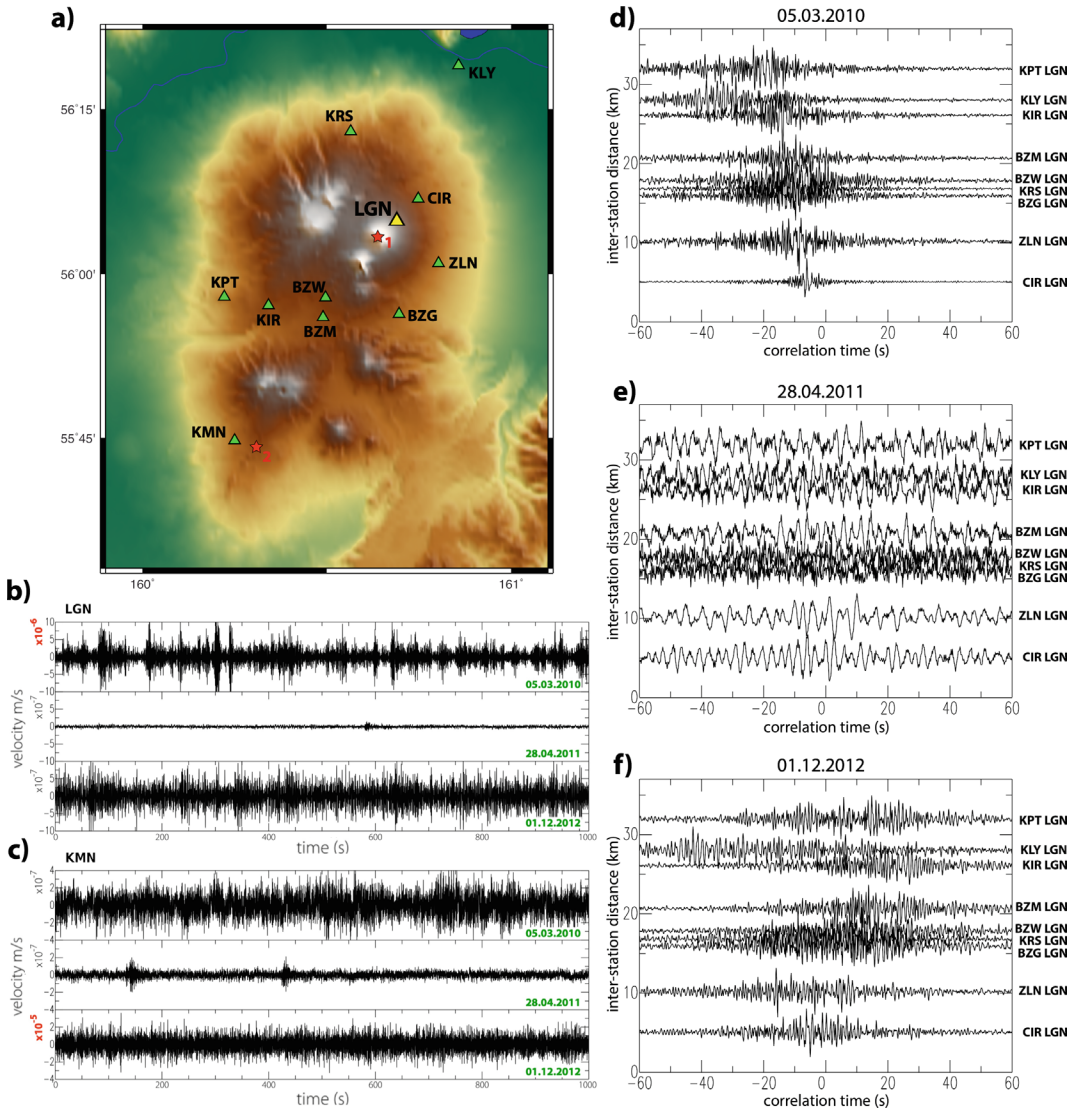


Fig. 6 Continuous time series and inter-station cross-correlation functions at the Klyuchevskoy Group of Volcanoes (KVG) in Kamchatka, Russia. Modified from Droznin et al. (2015). Non-filtered records by short-period seismographs with corner frequency of 0.8 Hz are shown and used in the analysis. **a** KVG topographic map. Triangles show the position of seismic stations. Red stars indicate the location of the 2009–2010 Kyuchevskoy (1) and of the 2012–2013 Tolbachik (2) eruptive centres. **b** and **c**

Examples of continuous records from vertical component of stations LGN and KMN, respectively. Corresponding dates are indicated with green numbers (records start at 00:00:00 UTC). Note the differences in the vertical scales as indicated with red numbers. **d–f** Cross-correlations of day-long vertical component records between stations LGN, shown with a yellow triangle in (a), and a set of other stations for dates illustrated in (b) and (c)

Kyuchevskoy and Tolbachik activity, the resulting correlation coefficients computed from sections between -40 and 40 s delineate the main periods of activity of these volcanoes. The reference

cross-correlation waveforms used for this “phase-matched” detection of tremors were selected arbitrary. With this approach, the efficiency of the detection could be deteriorated if the selected “ref-

erence” date was not representative of the most typical tremors. Figure 7e shows a matrix of correlation coefficients computed between all daily cross-correlations during the period of study. This matrix is symmetric and its rows (or columns) are equivalent to curves shown in Fig. 7c and d, with using different daily cross-correlation waveforms as references. The structure of this matrix clearly shows the separation between the activity of Klyuchevskoy and Tolbachik and, in addition, the possible existence of several clusters of similar cross-correlation waveforms likely corresponding to different sources of volcanic tremors. A more detailed analysis of these clusters and of the identification of their sources is presented in the following sections.

6 Network-Based Analysis of Seismic Tremor Wavefields

When a seismo-volcanic tremor is recorded by multiple stations of a network, the ensemble of inter-station cross-correlations provides us with a very convenient representation of the wavefield. This ensemble forms a network cross-correlation matrix (including auto-correlations) in the time domain and its equivalent in the spectral domain is the cross-spectral or covariance matrix. Therefore, in this section we will introduce the “network covariance matrix” - a mathematical object that is central in most of methods of network- or array-based signal analysis aimed at detection, separation, and location of seismic sources. In this section, we will consider some of these methods that are pertinent for the analysis of seismic tremors. At the same time, the network-based analysis is a very large field and the description presented in this section is not either complete or unique. Many methods or their variants are not considered here. Also, some methods described here (e.g., beamforming, back-projection) can be formulated in many different ways. The interested readers can find more details about the network-based analysis in specialized textbooks, web-sites, and scientific papers (some of which are included in the reference list).

6.1 Definition of the Network Covariance Matrix

In the following analysis we use conventions from Seydoux et al. (2016) and consider only vertical component records. Let’s consider the network data vector $\mathbf{u}(t) = [u_1(t) u_2(t) \dots u_N(t)]^T$, where $u_i(t)$ is the seismic trace registered by the seismometer i , N is the number of sensors and T denotes the transpose operator. Its Fourier transform in the frequency domain is $\mathbf{u}(f) = [u_1(f) u_2(f) \dots u_N(f)]^T$. From a mathematical point of view, the network covariance matrix $\mathbf{C}(f)$ is defined as the expected value of the cross-spectra product between $\mathbf{u}(f)$ and its transposed complex conjugate :

$$\mathbf{C}(f) = \mathbf{E} \left[\mathbf{u}(f) \mathbf{u}^\dagger(f) \right] \quad (12)$$

where $\mathbf{E}$ stands for the Expected Value and $\dagger$ denotes the Hermitian transpose (complex conjugate transpose). The network covariance matrix is inherently Hermitian and positive semidefinite. Therefore, it is diagonalizable and can be decomposed on the basis of its complex eigenvectors associated with real positive eigenvalues.

When working with real data, the estimation of the network covariance matrix requires several steps. First, the used seismic records must be pre-processed to enhance certain types of signals that are targeted in the analysis and to diminish a possible influence of “non-desired” signals, as detailed in Sect. 6.2. In a second step, inter-station covariances of pre-processed records are statistically estimated as described in Sect. 6.3.

6.2 Pre-processing of Seismograms

Standard preparation of the digital seismograms for the network-based analysis generally includes: instrument correction (preceded by both detrending and tapering), decimation (to reduce the data volumes and the amount of computations), sample alignment, managing the data gaps and overlaps, and organizing the records in segments of proper lengths.

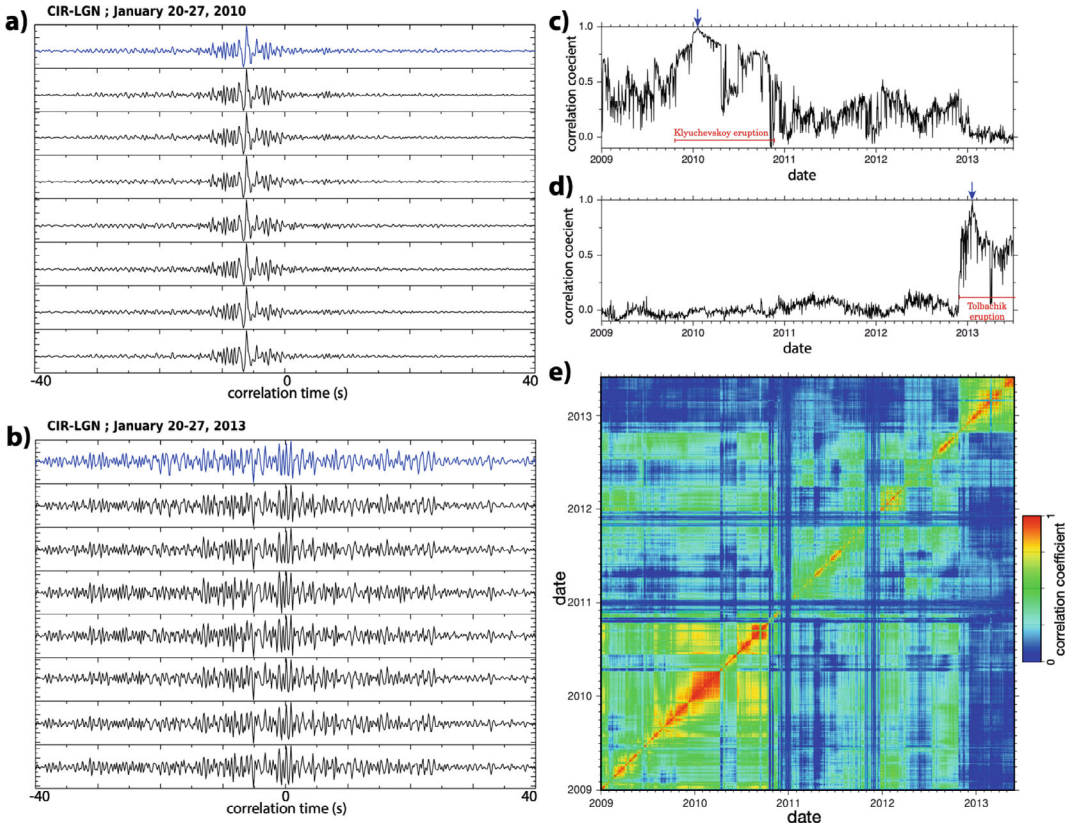


Fig. 7 Cross-correlations as fingerprints of volcanic tremor sources. Modified from Droznin et al. (2015). **a** Daily cross-correlations for station pair CIR-LGN during the Klyuchevskoy eruption: between January 20 and January 27, 2010. **b** Daily cross-correlations for station pair CIR-LGN during the Tolbachik eruption: between January 20 and 27, 2013. **c** Correlation coefficient between all daily cross-correlations and the reference cross-correlation waveform corresponding to the Klyuchevskoy eruption (the cross-correlation on January 20, 2010 shown with the

blue colour in (a) and indicated with the blue arrow). **d** Correlation coefficient between all daily cross-correlations and the reference cross-correlation waveform corresponding to the Tolbachik eruption (the cross-correlation on January 20, 2013 shown with the blue colour in (b) and indicated with the blue arrow). **e** Matrix of correlation coefficients between all daily cross-correlation waveforms for the station pair CIR-LGN. Eruption time intervals of Klyuchevskoy and Tolbachik volcanoes are indicated with horizontal red lines in (c) and (d)

Then, a specific pre-processing aimed at analyzing volcanic tremors is needed. Because of the continuous nature of the tremor signals, the pre-processing used for their analysis is very similar to the case of seismic noise (Bensen et al. 2007). It may start with filtering signals in the frequency bands corresponding to tremors. Then, the amplitudes could be normalized in both time and spectral domains. The time domain normalization is important to diminish the influence of earthquakes and other strong impulsive signals in order to emphasize the network-wide coherence of the

wavefield formed by long-duration tremors. At the same time, for some types of intermittent tremors the amplitude modulation might be a very distinctive and important feature. In this latter case, the amplitude normalization in time might be omitted (Soubestre et al. 2018). The spectral domain normalization is important to compensate for the dominance of most intense spectral peaks that are often present in tremors (Chouet 1996). Without normalization, these peaks might be strongly amplified in the covariances where the spectral amplitude is squared (Eq. 9).

Spectral whitening consists in dividing the signal spectrum by a smooth version of its amplitude:

$$u^W(f) = \frac{u(f)}{\langle\langle |u(f)| \rangle\rangle_{df}} \quad (13)$$

where $|u(f)|$ represents the real absolute value of the spectrum, and $\langle\langle \cdot \rangle\rangle_{df}$ stands for the smoothing in the frequency domain with a running window of a df length. The normalization is done similarly in the time domain:

$$u^N(t) = \frac{u^W(t)}{\langle\langle |u^W(t)| \rangle\rangle_{dt}} \quad (14)$$

where $u^W(t)$ is the real part of the inverse Fourier transform of $u^W(f)$, and $\langle\langle \cdot \rangle\rangle_{dt}$ is the smoothing in the time domain with a running window of a dt length. If no smoothing is applied ($df, dt = 0$), the amplitude information in the initial data is completely ignored.

6.3 Estimation of the Network Covariance Matrix

We estimate the covariance matrix $\mathbf{C}(f)$ from the time average of the Fourier cross-spectra matrices computed over a set of M overlapping subwindows of length δt (see Fig. 8). Filtered and decimated traces form the network data vector of one-component (vertical or horizontal) data $\mathbf{u}(t) = [u_1(t) \ u_2(t) \ \dots \ u_N(t)]^T$, where t is the time, $u_i(t)$ is the trace at station $i = 1, \dots, N$ and N is the number of sensors composing the network. The data vector is subdivided into overlapping time windows (generally with 50% of overlap), within which amplitudes are normalized (independently for each station). Every pre-processed window starting at a specific time t is then subdivided into M overlapping subwindows (generally with 50% of overlap) of duration δt , on which $\hat{\mathbf{u}}_m(f, t + m\delta t/2) \hat{\mathbf{u}}_m^\dagger(f, t + m\delta t/2)$ cross-spectra matrices are computed, where $m = 0, \dots, M - 1$; $\dagger$ denotes the Hermitian transpose (complex conjugate transpose); and $\hat{\mathbf{u}}_m(f, t + m\delta t/2)$ is the Fourier transform of the pre-processed data vector $\mathbf{u}_m(t + m\delta t/2)$. A

network covariance matrix $\mathbf{C}$ is then estimated on each pre-processed window starting at time t and with duration $\Delta_t = r(1 + M)\delta t$. This estimation corresponds to an average of the cross-spectra matrices computed on the M overlapping subwindows:

$$\mathbf{C}(f, t) = \frac{1}{M} \sum_{m=0}^{M-1} \hat{\mathbf{u}}_m(f, t + m\delta t/2) \hat{\mathbf{u}}_m^\dagger(f, t + m\delta t/2) \quad (15)$$

It is important to remember that the estimation of the network covariance matrix with Eq. (15) is strongly non-unique and depends both on the pre-processing of the raw data and on the parameters used in the averaging (number M and length δt of subwindows). Depending on the nature of the targeted signals, the choice of these parameters can be very different. For continuous and near-stationary tremors, a pre-processing removing the influence of amplitudes together with large number of long time windows might be used. On the contrary, for shorter signals, keeping the amplitude information and using shorter averaging time might be necessary.

The network covariance matrix (15) being inherently Hermitian and positive semidefinite (Seydoux et al. 2016), it can be decomposed on the basis of its complex eigenvectors $\mathbf{V}_i$ associated with real positive eigenvalues λ_i :

$$\mathbf{C}(f, t) = \sum_{i=1}^N \lambda_i(f, t) \mathbf{V}_i(f, t) \mathbf{V}_i^\dagger(f, t) \quad (16)$$

In the following paragraphs we will discuss how the network covariance matrix can be used for small-aperture array analysis (6.4), while the distribution of its eigenvalues can be used for tremor detection (6.5), whereas the first eigenvector can be used for separating (6.6) and locating (6.7) different tremor sources.

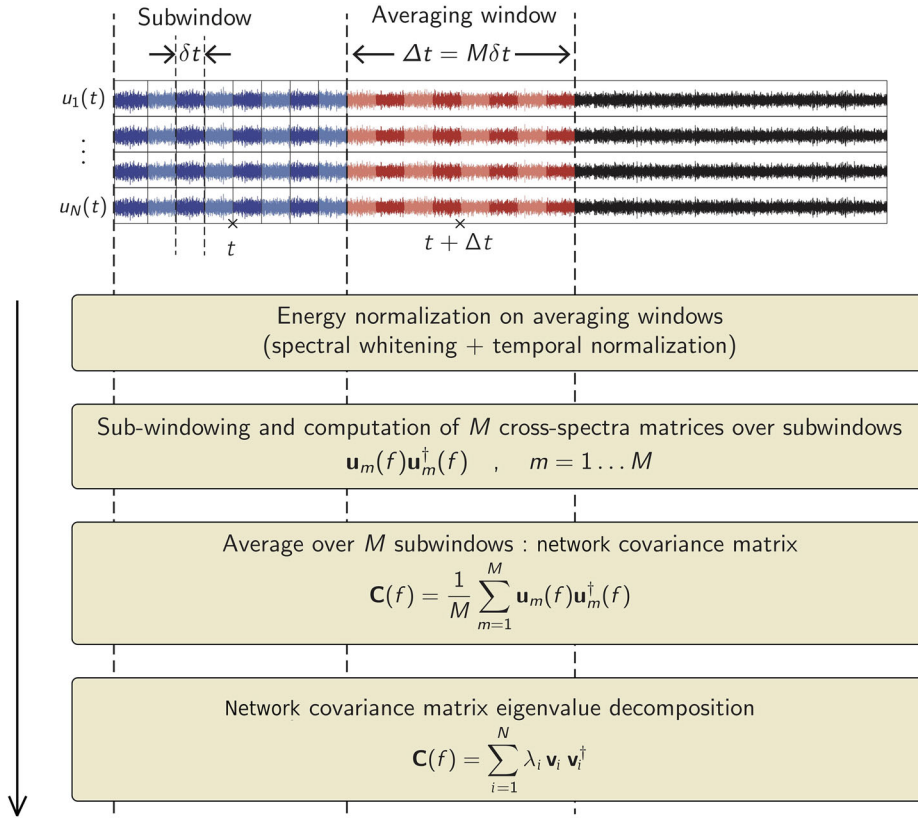


Fig.8 Sequence of operations used for estimating the network covariance matrix from continuous seismic records. Modified from Seydoux et al. (2016)

6.4 Beamforming of Volcanic Tremor with Small-Aperture Arrays

A seismic array is a group of seismic stations with inter-station distances being smaller than a half-wavelength of the studied signal. Indeed, when measuring a propagating waveform of a seismic signal using an array, its configuration and sensors spacing define a spatial sampling rate, which has to be higher than half of the considered signal wavelength in order to avoid spatial aliasing. Such spatial aliasing thus occurs when the seismic wavefield spatial variations are not well resolved by the array, leading to distortions and inaccuracies in the estimated locations and characteristics of the tremor sources. In volcanoes, a seismic array generally contains between five and a few tens of seismometers. The array aperture is typically a few hundreds of meters, with intersta-

tion distances of a few tens of meters. We note that the array aperture defines its resolution for small wavenumbers and it should be larger than the largest considered wavelength so that the corresponding seismic signal can be meaningfully analyzed (Schweitzer et al. 2012).

One advantage of arrays compared to single station analysis is the improvement of the signal-to-noise ratio (SNR) thanks to the summation of individual recordings of the array stations (Rost and Thomas 2002). More importantly, arrays can be used for beamforming providing knowledge about the direction of propagation of tremor waves (azimuth) and their velocity (or its inverse, the slowness). These parameters can then be used to determine the source location, especially by combining results from multiple arrays.

The array analysis is based on the assumption that the source is located outside of the array and

at a distance exceeding its aperture. In this case, the incoming wavefield can be approximated as a plane wave described by a slowness vector $\mathbf{p}$, or by its absolute value p and azimuth θ . Then, the differential travel times δt_{ij} between array elements i and j are related to their respective known positions $\mathbf{r} = (x, y)$ by the following equation:

$$\delta t_{ij} = \mathbf{p} \cdot (\mathbf{r}_i - \mathbf{r}_j) = p [(x_i - x_j) \cos \theta + (y_i - y_j) \sin \theta] \quad (17)$$

If the ensemble of inter-station travel times is measured, for example from the “ballistic” part of the inter-station cross-correlations (11), Eq. (17) can be used to estimate the azimuth and the slowness of the incoming wave. However, measuring these travel times with a visual analysis of cross-correlation waveforms might be not simple because of their complexity (see Fig. 6) and not practical for an extensive analysis of continuous data. Therefore, the practical implementation of the array analysis is often based on the plane-wave beamforming, that is aimed to estimate the parameters of the slowness vector directly from the continuous records (or their covariances) and whose basic mathematical expression can be derived by projecting the covariance matrix (15) on the functional sub-space formed by plane wave replicas:

$$\mathbf{b}(f, p, \theta) = \exp(2i\pi f p [\mathbf{x} \cos \theta + \mathbf{y} \sin \theta]) \quad (18)$$

where f is the frequency, and $\mathbf{x}$ and $\mathbf{y}$ are the vector of coordinates of the array sensors. The beamforming $\mathbf{B}(f, t, p, \theta)$ is then defined as:

$$\mathbf{B}(f, t, p, \theta) = \mathbf{b}^\dagger(f, p, \theta) \mathbf{C}(f, t) \mathbf{b}(f, p, \theta) \quad (19)$$

The retrieved distribution of energy on the slowness-azimuth plane can be used both for detection of tremors and for estimating the parameters of the slowness vector at its maximum. The basic idea of many detectors is to identify whether a clear peak corresponding to a tremor source is present or not in $\mathbf{B}(f, t, p, \theta)$. It is important to mention that Eqs. (18) and (19) present only one version of the plane-wave beamforming while many others not considered here exist (see Rost

and Thomas 2002, for a review of beamforming methods).

In order to evaluate the sensitivity and resolution of an array for seismic signals with different frequency contents and slowness, the array response function (ARF) is defined such as the beampower for a given plane-wave model, array configuration and beamforming method (Schweitzer et al. 2012; Ruigrok et al. 2017). The ARF quantifies how seismic waves arriving at different sensors are combined and weighted, and it can be computed prior to the actual array installation to assess and optimize the detection, localization and characterization of seismic sources.

It is also possible to use other replicas than plane wave replicas. In particular, when sources are located within or in the vicinity of an array, spherical or cylindrical replicas can be used. A more advanced version is to use replicas based on travel times predicted in a heterogeneous medium model. All this gives rise to a family of methods known as matched field processing (e.g., Baggeroer et al. 1988; Kuperman and Turek 1997; Almendros et al. 1999; Nanni et al. 2021).

Different versions of the beamforming with small arrays have been used to track the sources (or more exactly the back-azimuth and the apparent slowness of the recorded wavefield) of tremors and other types of seismicity in different volcanoes. Almendros et al. (1997) studied the time evolution of both volcanic tremor and hybrid events at Deception Island, Antarctica. The tremor was found to be composed of overlapping hybrid events. Highly coherent harmonic tremor was also studied by Almendros et al. (2014) at Arenal volcano. It was characterized by stable apparent slowness vector estimates, with backazimuths generally pointing towards the volcano. Furumoto et al. (1990, 1992) located the source of tremor at Izu-Oshima volcano, Japan. Tremor sources composed of discrete pulses were located at Mt Etna (Seidl et al. 1981), Stromboli (Chouet et al. 1999), Mt Aso (Kawakatsu et al. 1994, 2000), Mt Erebus (Rowe et al. 2000) and Iwate (Nishimura et al. 2000). Seismic surface waves coming from the crater of a volcano were associated with a shallow tremor source

at Kilauea (Ferrazzini et al. 1991; Saccorotti et al. 2003), Masaya (Métaxian et al. 1997), and Stromboli (Chouet et al. 1998). The array analysis enabled to identify three co-eruptive tremor sources associated with opening of new vents, growing margins of the lava field and intrusions during the 2014-2015 Holuhraun eruption in Iceland (Eibl et al. 2017a). It was also used to study shallow tremor close or beneath beneath Puu Oo crater (Goldstein and Chouet 1994) and Halemaumau crater (Almendros et al. 2001) at Kilauea volcano, Hawaii.

The intersection of backazimuth directions obtained at different arrays provides a joint location of the tremor source in the horizontal plane (2-D location). This technique has been used with different number of arrays. *Two arrays* were used to locate shallow tremor beneath Puu Oo crater at Kilauea volcano (Goldstein and Chouet 1994), shallow permanent tremor at Masaya volcano (Métaxian et al. 1997), volcanic tremor preceding and accompanying the 2004-2005 eruption of Etna volcano (Di Lieto et al. 2007), and tremor related to sub-glacial floods from draining glacier-dammed lakes in Skafta cauldrons at Vatnajökull glacier, Iceland (Eibl et al. 2020). A tremor source was located with *three arrays* close to Halemaumau crater at Kilauea volcano (Almendros et al. 2001). Finally, a tremor location centered on the active crater was obtained with *four arrays* at Arenal (Métaxian et al. 2002). Once the 2-D location obtained, the tremor source depth can be estimated if a 1-D velocity model is available (Almendros et al. 2001).

Smith and Bean (2020) recently provided a python-based software called RETREAT that uses seismic array data and array processing techniques to compute backazimuth and slowness in near-real time in order to improve tremor sources tracking and monitoring capabilities.

6.5 Detection of Tremor Based on Distribution of Eigenvalues of the Network Covariance Matrix

The small aperture arrays described in previous paragraphs can be installed during dedicated (and often relatively short-duration) field experiments. Maintaining such dense arrays for the routine continuous monitoring of volcanoes is not practical. Seismic monitoring networks operated by volcano observatories are rather extended over relatively large territories to cover different possible sources of seismicity. As a result, inter-station distances are much larger than wavelengths and, more importantly, most of tremor sources are located inside the networks. With such configuration, the plane-wave beamforming cannot be used and other methods need to be applied.

A first idea is to use the distribution of eigenvalues of the covariance matrix expressed as Eq. (16). It can be argued (e.g., Gerstoft et al. 2012; Seydoux et al. 2016), that if a wavefield is generated by a single source, the rank of the resulting covariance matrix will be equal to one. For K spatially separated and statistically independent sources, the matrix will be of rank K . This implies that the rank of the covariance matrix could be used as a proxy for the number of sources. However, using the rank of the covariance matrix is not practical because in the presence of noise it will be always non-zero. Therefore, the distribution of eigenvalues must be analysed in order to determine if one (or a few) of them dominates, which would be the case of one (or a small number of) tremor source, or if the distribution is rather “flat”, which would be the case of noise excited by many incoherent sources.

Based on these arguments, a scalar parameter $\sigma(f, t)$ called “spectral width” introduced by Seydoux et al. (2016) and defined as the width of the distribution of eigenvalues (with eigenvalues sorted in decreasing order) can be used to automatically detect tremor:

$$\sigma(f, t) = \frac{\sum_{i=1}^N (i-1) \lambda_i(f, t)}{\sum_{i=1}^N \lambda_i(f, t)} \quad (20)$$

This spectral width may be viewed as a proxy for the number of independent seismic sources composing the wavefield. Thus, the spectral width corresponding to ambient seismic noise composed of uncorrelated signals (with random phases) produced by spatially distributed noise sources would be relatively large. Conversely, the spectral width of a signal generated by a single localized source would be small.

The time-frequency-dependent spectral width $\sigma(f, t)$ computed from four and a half years of data (from January 2009 to May 2013) recorded by a network composed of 19 stations deployed at the Klyuchevskoy Volcanic Group in Kamchatka is shown in Fig. 9. Each pixel of this time-frequency plot represents the spectral width at a given time and frequency. This plot obtained from a network-based approach is therefore distinct from a spectrogram, which is related to the signal amplitude at an individual station and might be strongly affected by site effect. Spatially coherent signals (in terms of phase) of the wavefield appear with low spectral width value (red color) in Fig. 9, and periods dominated by uncorrelated noise appear with high spectral width value (blue color). Thus, the two months-long signals detected in the frequency range 0.4–3.0 Hz in 2009–2010 and 2012–2013 correspond to volcanic tremor (more details can be found in Soubestre et al. (2018)).

The spectral width is a very efficient and robust detector of tremors and does not depend on any assumption about the source location and type of emitted waves (as it must be done in the case of beamforming). At the same time, this simple scalar parameter is not sufficient to distinguish different tremor sources. In the particular case of KVG, it is not possible to know whether the 2009–2010 and 2012–2013 tremors detected in Fig. 9 correspond to the same tremor source at a given volcano activated at different periods, or to different sources at a single or multiple volcanoes. In the present case, the association of 2009–2010 and 2012–2013 tremors to Klyuchevskoy and Tolbachik volcanoes, respectively, is inferred from a priori knowledge (Droznin et al. 2015). But for this distinction to be automatically integrated into the network covariance matrix analysis, it is necessary to analyze the eigenvectors of the covari-

ance matrix and particularly the first eigenvector, as detailed in Sects. 6.6 and 6.7.

6.6 Distinguishing Between Different Sources of Tremor

As discussed in Sect. 5, inter-station cross-correlations contain a rich information that can be used to distinguish different sources of seismic tremor not only based on their spectral content but more importantly based on signatures of the seismic wave propagation from different locations that are contained in the phase of the cross-correlation waveforms (or cross-spectra). The eigenvalue-based analysis described in previous paragraphs ignores this phase information that is contained in the eigenvectors of the network covariance matrix expressed as Eq. (16). Here we use the first eigenvector $\mathbf{V}_1(f, t)$ that characterizes the dominant source of the seismic tremor as a “fingerprint”. This can be considered as an extension of the approach based on a single-pair cross-correlation (Sect. 5) to a whole network.

Eigenvectors of the matrix (16) are complex and defined in the spectral domain. Therefore, to characterize their level of similarity, we introduce a correlation coefficient $cc_{k,l}(f)$ between the first eigenvectors from windows k and l : $\mathbf{V}_1(f, t_k)$ and $\mathbf{V}_1(f, t_l)$. These vectors being complex, the correlation coefficient is defined at each frequency as the absolute value of the complex scalar product normalized by the respective norms:

$$cc_{k,l}(f) = \frac{|\mathbf{V}_1(f, t_k) \mathbf{V}_1^*(f, t_l)|}{\|\mathbf{V}_1(f, t_k)\| \|\mathbf{V}_1(f, t_l)\|} \quad (21)$$

Then, an average correlation coefficient $\overline{cc}_{k,l}$ is computed as the mean of the n_f correlation coefficients calculated in a selected frequency band between f_1 and f_2 :

$$\overline{cc}_{k,l} = \frac{1}{n_f} \sum_{f_1}^{f_2} cc_{k,l}(f) \quad (22)$$

An ensemble of such average correlation coefficient computed between all time windows forms

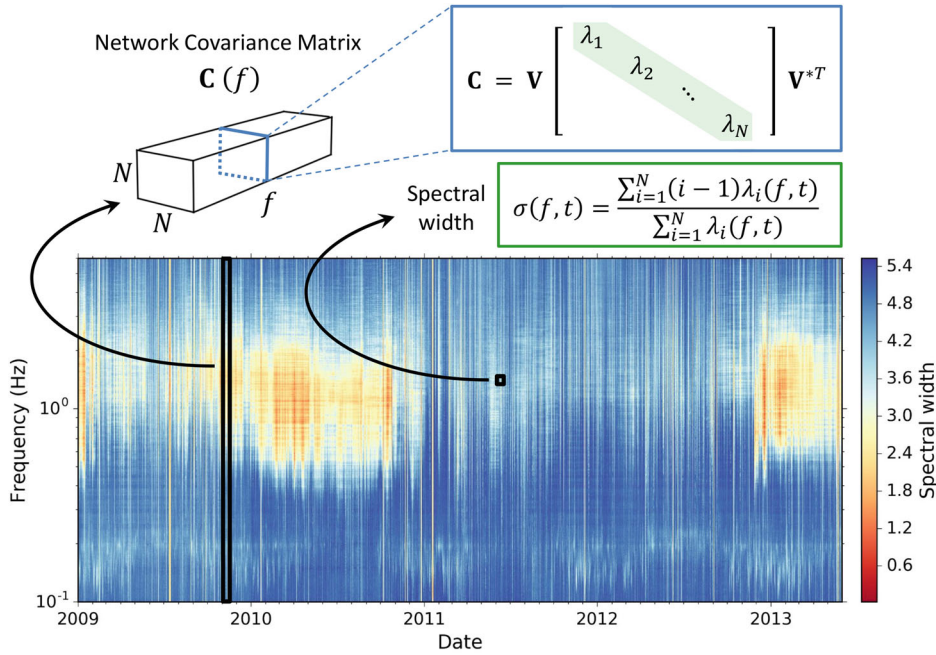


Fig. 9 Detection of tremors at KVG with the network covariance matrix method. Modified from Soubestre et al. (2018). Time-frequency-dependent spectral width computed from four and a half years of data recorded by a network composed of 19 stations deployed at the Klyuchevskoy Volcanic Group in Kamchatka. It is computed with the following parameters explained in Sect. 6.3: time windows of length $\Delta_t = 25,000$ s composed of $M =$

50 subwindows of length $\delta_t = 1,000$ s overlapping at 50 %. The network covariance matrix and the spectral width corresponding to a time window and a pixel of the plot, respectively, are shown on top of it. The two months-long signals detected in the frequency range 0.4–3.0 Hz in 2009–2010 and 2012–2013 correspond to volcanic tremor from Klyuchevskoy and Tolbachik volcanoes, respectively, as inferred from a priori knowledge (Droznin et al. 2015)

a matrix. An example of such matrix computed from the KVG monitoring seismic network during 2009–2013 is shown in Fig. 10a. In this case, day-long inter-station cross-correlations have been used and the correlation coefficient has been averaged between 1 and 2 Hz. This matrix has a structure that reveals several periods of elevated similarity between distinct days, implying that the dominating tremor source remained stable during those periods. It resembles the one based on just one pair of stations (Fig. 7e) but with some clusters of activity being better isolated because of using all possible station pairs.

Different sources of tremor can be identified from matrix (22), for example, with a similarity-based clustering algorithm described in Soubestre et al. (2018). It works in two steps: (1) selection of initial clusters and (2) iterating and resorting to obtain the final clusters.

The first step contains three stages. First, correlation coefficients $\overline{cc}_{k,l}$ are averaged in time in a moving window. The window duration might be selected as approximately equal to the lower limit of duration of considered tremor episodes. In the case of KVG, we used a 20-day-long window, thus aimed at rather long continuous tremors. When analysing intermittent tremors (e.g., Fujita 2008; Cannata et al. 2010), a shorter window might be more adequate. A result of this operation is shown with a black line in panel 2 of Fig. 10a. The maximum of this averaged correlation coefficient determines the initial cluster central window (vertical red line in panel 2, Fig. 10a), called centroid. Second, the line (or column) of the average correlation coefficients matrix corresponding to this centroid is considered (black line in panel 3, Fig. 10a) and only the windows with a correlation higher than a given threshold s_{cc} (red line in panel 3,

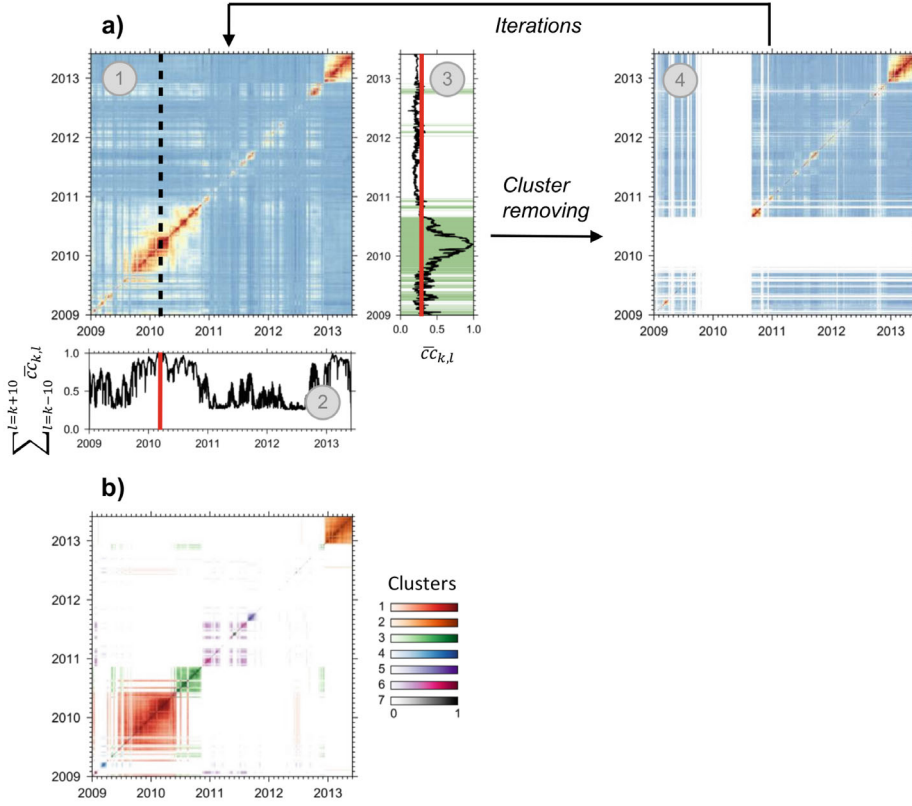


Fig. 10 Clustering of tremors at KVG with the network covariance matrix method. Modified from Soubestre et al. (2018). **a** Iterative procedure of identification of clusters, as detailed in Sect. 6.6. **a-1** Matrix of correlation coefficients computed between dominant eigenvector (Eq. 22). One-day-long time windows and 1–3 Hz spectral band have been used. **a-2** Finding a centroid of the

first cluster. **a-3** Selecting days with similar first eigenvectors. **a-4** Removing the first cluster from the matrix. **b** Time-time representation of the final seven clusters associated with tremor activity at four different volcanoes based either on a priori knowledge or on locating tremor sources (Sect. 6.7). Color scales correspond to correlation coefficient relative to the cluster centroid

Fig. 10a) are kept in the cluster (green rectangles in panel 3, Fig. 10a). Third, windows corresponding to this cluster are removed from the matrix (panel 4, Fig. 10a) and the process is continued iteratively up to the determination of the n_{clus} initial clusters.

The second step consists in resorting the initial clusters. It is realized in an iterative way. Each iteration of resorting contains two stages. First, the centroid of each of the n_{clus} initial clusters is redefined by time stacking the coefficients $\overline{cc}_{k,l}$ not anymore through a n_{days} -long moving window, but through a window containing only the days of the concerned cluster determined in the

first step. Second, each day of the studied period (from January 2009 to May 2013 in the case shown in Fig. 10) is compared to those n_{clus} redefined centroids (second step, first stage) and placed in the cluster where the correlation is the highest. With the parameters $n_{clus} = 10$, $n_{days} = 20$ and $s_{cc} = 0.3$ used in the example shown in Fig. 10a, it takes three iterations for the iterative process to converge, i.e. for the redefined centroids to not change between two consecutive iterations.

Note that once the window duration n_{days} fixed, the clustering result is not very sensitive to the values of parameters s_{cc} and n_{clus} . The latter just needs to be higher than the potential number

of distinct tremor sources. Here $n_{clus} = 10$ is adapted to the case of KVG with several erupting volcanoes and episodes of activity, but a smaller value could be used in less active volcanic systems.

Figure 10b shows the first seven clusters associated with tremor activity (the remaining three clusters are associated with noise). In addition to the two tremor episodes in 2009–2010 and 2012–2013 already detected by the spectral width approach in Fig. 9, other time periods related to tremor activity are highlighted by the clustering approach, in particular in 2011. Based on a priori knowledge, four volcanoes were active during the 2009–2013 studied period, namely Klyuchevskoy, Tolbachik, Shiveluch and Kizimen. The seven clusters are therefore associated with the activity at those four volcanoes. Given that a specific tremor source is supposed to be associated with each cluster, different clusters are necessarily associated with a single volcano. Possible explanation of this is either that the tremor-generating activity migrated or that the tremor-generating process changed. In particular, additional analysis show that clusters 1 and 3 of Fig. 10b are associated with noneruptive tremor and eruptive tremor at Klyuchevskoy, respectively (Soubestre et al. 2018). Note that being based on the scalar parameter $\overline{cc}_{k,l}$ removing the space information and containing only the time dimension (cf. Eqs. (21) and (22)), the clustering approach described here is able to distinguish tremor sources in time but not in space. For the distinction in both time and space to be automatic and integrated to the network covariance matrix analysis, it requires to keep the spatial information contained in the first eigenvector, as in the location approach detailed in the following sections.

6.7 Covariance-Based Location of Tremor Sources

Methods of volcanic tremor sources location from network cross-correlations have been proposed in different studies (e.g., Ballmer et al. 2013; Droznin et al. 2015; Soubestre et al. 2019; Li and Gudmundsson 2020). The

common idea is to use the differential travel times contained in inter-station cross-correlations (Eq. 11) in order to “back-project” the tremor signals energy toward its source. Often, tremor sources are considered as a priori shallow and cross-correlations are assumed to be dominated by surface waves. This assumption leads to a 2-D location scheme. However, in many cases tremor sources are located at significant depths (more than a few km) and in this case a 3-D back-projection based on a body-wave (most often S-wave) assumption must be implemented. The network covariance matrix formalism also allows to better isolate contribution from the dominant tremor source via selecting the first eigenvector which leads to a slightly more accurate location (Soubestre et al. 2019). An important limitation of the location method presented in this section is the assumption of a single dominating source leading to a single dominant eigenvalue/eigenvector. In the case of multiple simultaneously acting sources, a more advanced approach should be developed with analyzing several eigenvectors in order to separate the different sources.

The filtered covariance matrix $\tilde{\mathbf{C}}(f, t)$ is extracted from Eq. (16) by computing the complex outer product of the first eigenvector $\mathbf{v}^{(1)}(f, t)$ with its Hermitian transpose:

$$\tilde{\mathbf{C}}(f, t) = \mathbf{v}^{(1)}(f, t) \mathbf{v}^{(1)\dagger}(f, t) \quad (23)$$

This operation can be seen as a low-rank denoising of the covariance matrix, a strategy widely used in image processing to remove the noise spanned by higher-order eigenvectors (Orchard et al. 2008). The inverse Fourier transform of this matrix retrieves the time-domain filtered cross-correlations:

$$\tilde{\mathbf{C}}\mathbf{C}(\tau, t) = \mathcal{F}^{-1} \tilde{\mathbf{C}}(f, t) \quad (24)$$

where $\mathcal{F}^{-1}$ is the inverse Fourier transform operated to the frequency dimension, and τ is the cross-correlation lag-time. Non-diagonal elements of this matrix $\tilde{\mathbf{C}}\mathbf{C}_{i,j}(\tau, t)$ are the “filtered” inter-station cross-correlations.

These cross-correlations are then “back-projected” to find the tremor source position. This back-projection is realized as a grid search in a 3-D space. First, all points of the grid $\mathbf{r}$ are considered as potential sources, and travel times $\tau_i(\mathbf{r})$ to all stations (i) of the network are predicted based on a known velocity model of the sub-volcanic medium. In most cases tremors are considered to be dominated by S-waves. Ideally, 3-D velocity models can be considered. However, in most volcanic areas, these are not accurate enough and average 1D velocity models lead to more robust location results. The smoothed amplitude envelopes $E_{i,j}(\tau, t)$ of $\tilde{C}C_{i,j}(\tau, t)$ are then computed and shifted with respect to differential travel times:

$$d\tau_{ij}(\mathbf{r}) = \tau_i(\mathbf{r}) - \tau_j(\mathbf{r}) \quad (25)$$

Finally, a network response function R is estimated as the value at zero lag-time of the sum of smoothed and shifted envelopes for all stations pairs:

$$R(\mathbf{r}, t) = \sum_{i=1}^N \sum_{j>i}^N E_{ij}(\tau - d\tau_{ij}(\mathbf{r}), t) \Big|_{\tau=0} \quad (26)$$

This version of back-projection does not involve a coherent summation of cross-correlation waveforms but of their smoothed amplitude envelopes. This reduces the alteration of the location quality from scattering due to local heterogeneities and from the imprecision of the location method itself, particularly the imprecision of the velocity model. Finally, the function $R(\mathbf{r}, t)$ can be interpreted as a spatial likelihood of the tremor source location and the most probable source position can be defined at its maximum. Examples of tremor sources located at KVG are shown in Fig. 11.

Tremor location error can be estimated by measuring the spatial distribution of high values of the spatial likelihood function above a certain threshold. For the Kamchatka tremor sources, this measurement shows an increase in vertical error from a few kilometers near the surface, to around 10 km towards 30 km depth (Journeau et al. 2022).

In addition, it can be useful to measure the distance between the hypocenter of an earthquake located using the P and S wave arrival times and the coordinates of the maximum of the spatial likelihood function calculated for a time window containing this earthquake. Permana et al. (2019) show that the resulting misfit is around 2 km or less using VT hypocenters below the Izu-Oshima volcano. This average misfit is about 7 km for DLP earthquakes located around 30 km below the Klyuchevskoy volcano (Journeau et al. 2022).

7 Application Examples

In addition to examples shown in previous sections, we illustrate the network-based analysis of seismic tremor with two studies of very active and well-instrumented volcanic systems. The first example is the 2018 Lower East Rift Zone eruption of Kilauea Volcano, Hawaii, that generated multiple sources of rather shallow tremor at the summit region in the Kilauea Caldera. The second example is from the Klyuchevskoy Group of Volcanoes in Kamchatka, Russia, where a large regional-scale network has been installed during 2015–2016 and recorded seismic tremors originating beneath different active volcanoes over a large range of depths from the crust-mantle boundary to the surface. In both cases, we discuss how the network-based analysis can be used to distinguish different sources of tremor and to test possible hypotheses about their origin.

7.1 Shallow Seismic Tremor at Kilauea Volcano, Hawaii

The present section describes an example of analysis of several shallow volcanic tremor sequences which accompanied the summit activity during the 2018 Lower East Rift Zone eruption of Kilauea Volcano, Hawaii. More details about this case study can be found in Soubestre et al. (2021). The eruption was marked by a dyke intrusion and the production of voluminous lava flows in the lower east rift. Magma withdrawal from the summit region induced summit subsidence and triggered

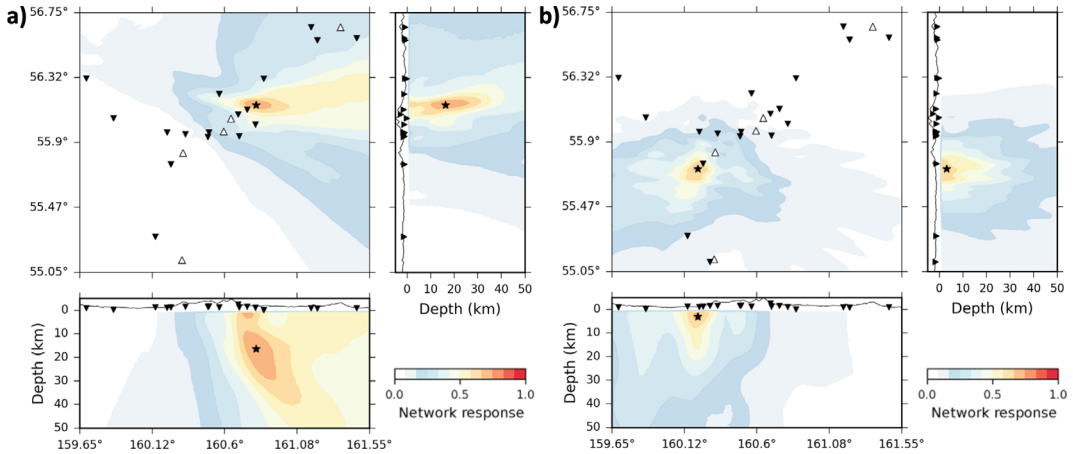


Fig. 11 Location of tremor sources at KVG with the network covariance matrix method. Modified from Soubestre et al. (2019). Colored contours show tremor source presence likelihood (Eq. (26) with envelopes smoothed in a 10-day-long window). The most probable tremor source location is marked by a black star. Seis-

mic stations and volcanoes respectively appear as black inverted triangles and white triangles in the horizontal top view (center panel). **a** Deep tremor beneath Klyuchevskoy on October 3, 2009. **b** Shallow tremor beneath Tolbachik on March 4, 2013

the draining of an active lava lake in the Halemau-mau Crater in the Kilauea Caldera. The surface of the lava lake started to drop on May 2, 2018 (Neal et al. 2018), synchronous with the onset of the summit steady subsidence associated with elastic decompression (Anderson et al. 2019). Over the intervening week the lava lake dropped more than 300 m, eventually vanishing from sight on May 10, 2018 (Neal et al. 2018). Sustained magma withdrawal induced a drop of the floor of Halemau-mau, which progressed in a series of 12 rapid semi-regular collapses corresponding to inelastic failures starting on May 17, 2018. As the eruption continued over the next three months, surface collapse grew beyond Halemau-mau to encompass large portions of the caldera to the east and west. A total of 62 collapse events occurred in the caldera up to early August when the summit subsidence and the emission of lava in the lower east rift essentially ceased. By August 2, 2018, the collapses had resulted in 5 km² of the caldera dropping between 120–470 m.

Volcanic tremor exhibited strong changes relative to the dynamic behavior at the summit of Kilauea as it evolved from steady state activity through April, to elastic subsidence in early May,

and inelastic collapses from mid-May onward (Anderson et al. 2019). The time-frequency-dependent spectral width $\sigma(f, t)$ computed from two months of data (from April 15 to June 15, 2018) recorded by a network composed of 12 broadband seismic stations deployed at the summit with an aperture of 5 km (Fig. 12e) is shown in Fig. 12a. The time series of a tiltmeter co-located with one of the seismometers on the northwest flank of Kilauea Caldera (station UWE, Fig. 12e) is shown as a black line superimposed on the spectral width plot. Distinct tremor sources identified in this figure are described below and discussed in more detail in Soubestre et al. (2021). The tremor sources are located with the method described in Sect. 6.7, on a 3-D grid covering the 8.4 km $\times$ 6.6 km summit region shown in Fig. 12b–d down to 6 km depth, with a 200 m resolution in both horizontal and vertical directions. Note that the low spectral width saturation clearly visible in the 0.1–0.3 Hz frequency band in Fig. 12a corresponds to some spatial aliasing due to the network size and prevents the oceanic microseismic noise from being correctly detected (Soubestre et al. 2021).

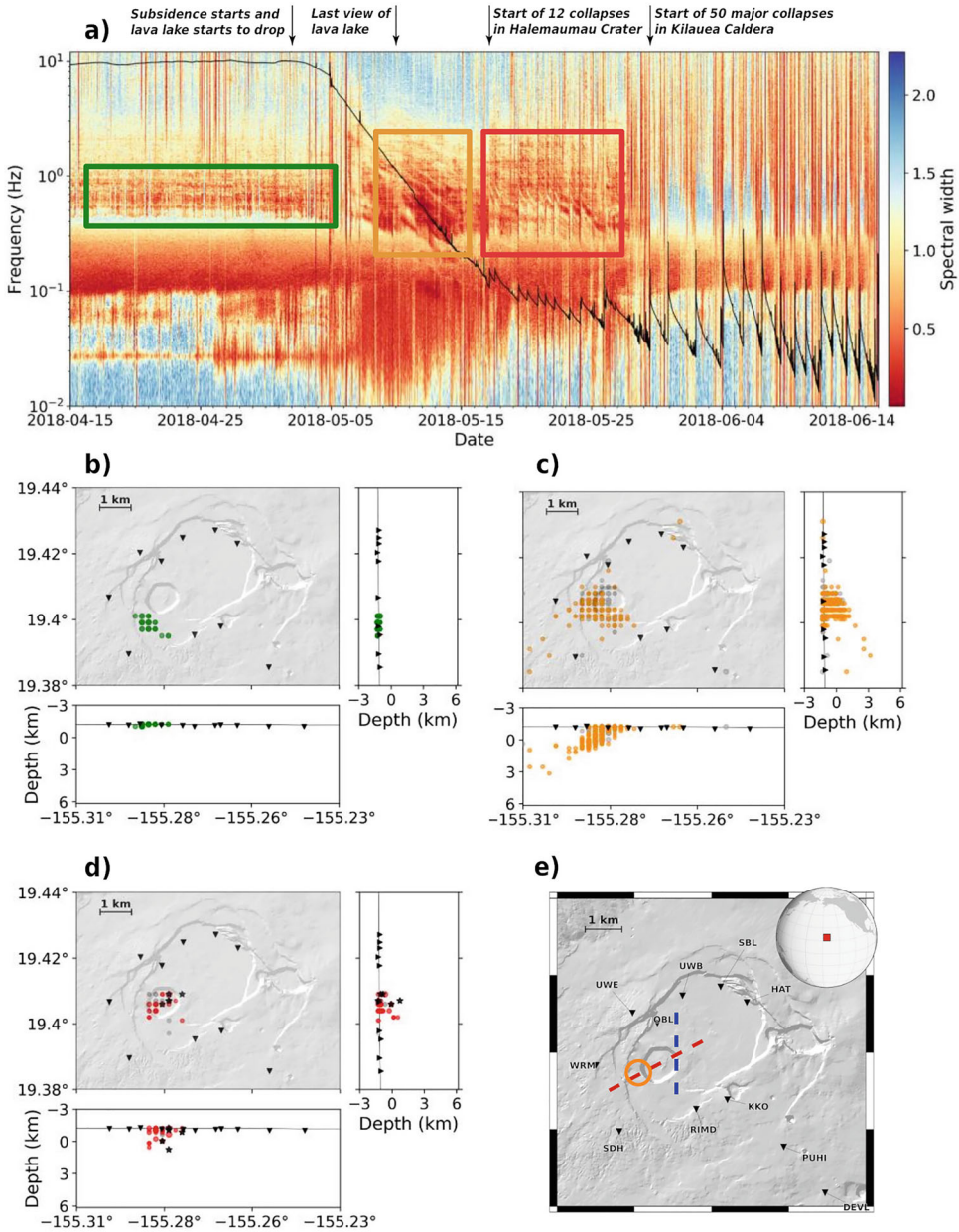


Fig. 12 Application example of shallow tremor characterization at Kilauea, Hawaii. Modified from Soubestre et al. (2021). **a** Time-frequency-dependent spectral width computed from two months of data recorded by a network composed of 12 broadband seismic stations deployed at the summit of Kilauea. It is computed with the following parameters explained in Sect. 6.3: time windows of length $\Delta_t = 500$ s composed of $M = 10$ subwindows of length $\delta_t = 100$ s overlapping at 50 %. The time series of a tiltmeter co-located with one of the seismometers on the northwest flank of Kilauea Caldera is shown as a black line

superimposed on the spectral width plot. Distinct tremor sources can be identified in this figure: long-period tremor before May 5 (green box), first sequence of gliding tremor between May 7 and May 16 (orange box), second sequence of gliding tremor between May 17 and May 27 (red box). Location of tremor sources corresponding to long-period tremor (**b**), first sequence of gliding tremor (**c**) and second sequence of gliding tremor (**d**). **e** Dykes (red and blue dashed lines) and collapse region (orange circle) discussed in the text. Seismic stations appear as black inverted triangles

Two very-long-period tremors are clearly detected in Fig. 12a at frequencies near 0.026–0.027 Hz (periods 37–38 s) and 0.060–0.070 Hz (periods 14–17 s). Those tremors are stable before May 5 and vanish during the period when the magma withdraws and the lava lake drops out of sight (May 10), evidencing their direct relation with the lava lake itself. Note that owing to the very long wavelength of those signals (on the scale of one hundred kilometers) compared to source-station distances (a few kilometers), the cross-correlation based location method described in Sect. 6.7 cannot be applied to locate their sources, because at such very low frequency all cross-correlations of the considered network turn to auto-correlations. Nevertheless, the 0.026–0.027 Hz and 0.060–0.070 Hz tremors have been well characterized in different studies and correspond to the breathing mode of the lava lake mass perched on top of a dual dyke plexus (Chouet et al. 2010; Chouet and Dawson 2011) and to sloshing modes of the lava lake (Dawson and Chouet 2014), respectively.

A stable long-period tremor is present in Fig. 12a in the frequency range 0.5–1.0 Hz before May 5 (green box, Fig. 12a). Source locations of this tremor for consecutive 6 h-long time windows point to a surficial source positioned at the south-southwest edge of the Halemaumau Crater (green dots, Fig. 12b). The source is bracketed by the east-striking and north-striking dykes in the dual dyke system imaged by Chouet and Dawson (2011) (red and blue dashed lines, respectively, Fig. 12e), where it sits approximately 200 m south of the surface trace of the east dyke and 500 m west of the surface trace of the north dyke. The proximity of these spatially extended heat sources, together with the presence of abundant meteoritic water in the caldera and the surficial character of this activity, are strongly suggestive of a hydrothermal origin. This tremor is therefore attributed to the quasi-steady radiation from a shallow hydrothermal system positioned at the south-southwest edge of Halemaumau Crater.

Two sequences of gliding tremor appear in the frequency range 0.3–3.0 Hz in Fig. 12a. The first sequence of gliding tremor occurs between May 7 and May 16 (orange box, Fig. 12a), when the

magma withdraws and the lava lake disappears (May 10). The second sequence occurs between May 17 and May 27 (red box, Fig. 12a), when the first 12 collapses occurred in Halemaumau Crater. A different interpretation of those two gliding tremors is sustained by four arguments: distinct continuous and discrete nature of the glidings, distinct surface activity observed during the two sequences, distinct spatial locations of the tremor sources, and distinct ratios of excited frequencies implying different physical models of their source processes.

The first sequence of continuous gliding tremor occurs between May 7 and May 16, just after the shallow hydrothermal system associated with the 0.5–1.0 Hz long-period tremor ceased its steady state activity and before the start of the 12 collapses that affected the Halemaumau Crater. Sources of this gliding tremor are located near the northwest, west, southwest, and south edges of Halemaumau Crater (orange dots, Fig. 12c). This gliding tremor is attributed to the progressive intrusion of a rock piston into the leaky hydrothermal system (following Kumagai et al. (2001) who modeled VLP signals associated with the caldera formation at Miyake Island with a rock piston intruding into the leaky magma chamber). This interpretation is supported by topographic images showing that the region west and southwest of Halemaumau was the first region outside of the crater to collapse in early June (orange circle, Fig. 12e), evidencing the potential weakening of this zone due to the presence of the hydrothermal system. It is further supported by the observation that most ejecta in steam plumes produced during this period were found to be lithic rock fragments, which is consistent with what is expected from the breaching of a hydrothermal system. The progressive sagging and intrusion of the rock mass into the hydrothermal reservoir generates swarms of low-amplitude regularly repeating earthquakes modeled by a Dirac comb effect. The spectral gliding characterized by the decrease of frequencies observed in the data corresponds to the decrease of the fundamental frequency and harmonics of the Dirac comb spectrum due to a progressive increase in the time interval τ

between successive earthquakes in the swarms (following Hotovec et al. (2013); Dmitrieva et al. (2013) who observed an opposite gliding trend towards higher frequency associated with accelerating earthquakes):

$$f_n = n/\tau \quad (27)$$

where n stands for the index of fundamental frequency ($n = 1$) and harmonics ($n \geq 2$), and $\tau = \tau_{stick} + \tau_{slip}$ is the stick-slip duration with τ_{stick} and τ_{slip} the duration of an individual downward piston movement and stuck piston, respectively. The stick-slip piston model is applied to two successive swarms with 55.5 and 90.5 h duration, during which the stick-slip duration τ increased from 2.23 s at 11:00 UTC on May 7 to 5.05 s at 05:30 UTC on May 14. Waveforms from individual earthquakes therefore overlap in time and cannot be distinguished in the seismic traces that look like continuous tremor (Hotovec et al. 2013; Dmitrieva et al. 2013). The modeled piston consists of a cylindrical rock mass of 2.07×10^{11} kg with radius of 325 m and height of 250 m progressively intruding 12.3 m through 169,466 small piston strokes into a shallow hydrothermal reservoir with volume of 10^8 m³ and depth extent of 300 m. The intruded volume represents 4.1 % of the reservoir initial volume (see Soubestre et al. (2021) for more details about the different estimates mentioned in this paragraph).

The second sequence of discrete gliding tremor occurs between May 17 and May 27, when 12 roof collapses took place within Halemaumau Crater (visible as pulses on the tilt signal in Fig. 12a). Sources of this gliding tremor are located within the crater (red dots, Fig. 12d) and coincide with the position of the 2.9 km $\times$ 2.9 km east-striking dyke imaged by Chouet and Dawson (2011) beneath the Halemaumau Crater (red dashed line, Fig. 12e). This gliding tremor is attributed to a change in the physical properties of the underlying east-trending dyke impacted by the collapses, which triggered the dyke resonance. The spectral gliding, which is manifested in a gradual lowering of the resonant frequencies of the dyke, is interpreted

as a decrease of the higher-mode frequencies of the resonating dyke associated with a progressive increase in crack stiffness C (Maeda and Kumagai 2017):

$$f_m = \frac{(m-1) v_s}{2L\sqrt{1+2\epsilon_m C}} \quad (28)$$

where m represents the mode number, v_s is the sound velocity of the fluid filling the dyke, ϵ_m is a constant dependent on the crack aspect ratio W/L (here equal to 1) and the mode number, and L and W are the crack length and width, respectively. Using the fluid-filled crack model of Chouet (1986), the increasing stiffness is related to a gradual decrease in the gas volume fraction within the bubbly melt filling the dyke. The gas volume fraction decreases from 4.22 % at the time of collapse #1 (04:15 UTC on May 17), to 1.6×10^{-2} % at the time of collapse #10 (02:15 UTC on May 25), with an associated increase in crack stiffness from 6 to 2620 between collapses #1 and #10, respectively. The temporal evolution of the gas volume fraction during the intervals between collapses is further investigated with a model of gas retro-diffusion. Both the fluid-filled crack model and gas retro-diffusion model are consistent with a quasi to totally degassed magma by the end of the sequence of 12 collapses that affected Halemaumau Crater through May 26 (see Soubestre et al. (2021) for more details about the different estimates mentioned in this paragraph).

7.2 Tremor in a Transcrustal Magmatic System: KVG, Kamchatka, Russia

The Klyuchevskoy Volcanic Group (KVG) located in the Russian Kamchatka peninsula is one of the World's largest and most active clusters of subduction volcanoes. During recent decades, three volcanoes erupted in this region: Klyuchevskoy, Bezymianny, and Tolbachik (Fig. 13c). Seismic tomography (e.g. Koulakov et al. 2020) and seismicity (e.g., Levin et al. 2014; Shapiro et al. 2017a) reveal a deep magmatic reservoir located at the crust-mantle boundary

and possibly connected to active volcanoes through a rifting zone developed after a recent subduction reconfiguration. This large-scale structure channels fluids and transfer pressure that play an important role in the activity of the KVG volcanoes and generate intense LP seismicity dominated by tremors. To analyse these tremors, we applied the network covariance matrix based method to 45 stations operated in the vicinity of the KVG (Fig. 13b) in the framework of the “Klyuchevskoy Investigation - Seismic Structure of an Extraordinary Volcanic System” experiment (KISS) (Shapiro et al. 2017b). We analyzed frequencies between 0.5 and 5 Hz and selected rather long time windows with length $\Delta t = 1200$ s (by fixing the number of subwindows at $M = 48$ and the subwindow length at $\delta t = 50$ s, as detailed in Sect. 6.3) to focus on seismic tremors.

Two main periods of reduced spectral width corresponding to intense seismic tremors can be seen in Fig. 13a. The first one started in the beginning of December 2015 and did not end with an eruption. It continued until mid-February 2016 when the activity partially migrated toward Tolbachik. The second episode corresponded to a subsequent activation that led to an eruption in April 2016. We applied a set of network-based criteria described in detail in Journeau et al. (2022) and selected 13,027 windows identified as tremors or swarms of LP earthquakes and located their sources. Their spatial and temporal distribution is shown in Fig. 13b–f.

The network-based location method described in Sect. (6.7) results in a spatial likelihood function (e.g., Fig. 11) computed on a 3-D grid covering the $55 \text{ km} \times 70 \text{ km}$ region shown by a black-dashed rectangle in Fig. 13b down to 50 km depth, with a 650 m horizontal resolution and a 500 m vertical resolution. To characterize the overall spatial distribution of the tremor sources, we stacked all these likelihood functions. The result shown in Fig. 13b–c delineates the active parts of the plumbing system. The highest source density is observed beneath the main part of the KVG including Klyuchevskoy, Bezmyanny, and Ushkovsky. A smaller number of sources are located beneath Tolbachik and

Udina. This suggests that the active plumbing system extends approximately 50 km along the rift structure (Koulakov et al. 2020) from southwest of Tolbachik volcano to north-east of Klyuchevskoy volcano. The vertical cross-section (Fig. 13c) shows that the active plumbing system extends through the whole crust, with the Moho-level magmatic reservoir being connected to Klyuchevskoy via a main conduit and to Tolbachik Udina volcano via a branch deviating at ~ 25 km depth.

The space-time distribution of the tremor hypocenters (Fig. 13d–f) is not fully random and is mainly composed of short bursts. A detailed view of these bursts reveals migration-like patterns when the activity moves very rapidly from depth toward the surface. We visually identified different upward and downward migration episodes and approximately represented them with simple linear trends (red arrows in Fig. 13e–f). The resulting migration velocities were approximately estimated between 3 and 10 km/h (Journeau et al. 2022). While, most of the time, the tremor activity occurs approximately beneath the Klyuchevskoy volcano, during a few episodes it migrates laterally toward Tolbachik.

The observed spatio-temporal patterns of tremor sources constrain the physical mechanisms controlling the evolution of the activity. Rapid migrations (red arrows, Fig. 13e–f) are unlikely to be explained by magma motion through dykes, because the observed migration speeds (up to 10 km/h) are faster than those associated with dyke propagation or other volcanic fluid migrations that have been reported to be smaller than 1 km/h in most of the cases. More importantly, observed downward migrations could not be explained by dyke propagation. These migration patterns are not perfectly aligned and have similarity with random diffusions that may be related to the physics of pressure transfer in a system of hydraulically connected magmatic conduits. Such mechanism has been previously evoked by Shapiro et al. (2017a) to explain the link between DLP and shallow LP earthquakes observed at the KVG, when the activity migrated over ~ 30 km from the Moho level up to the crust

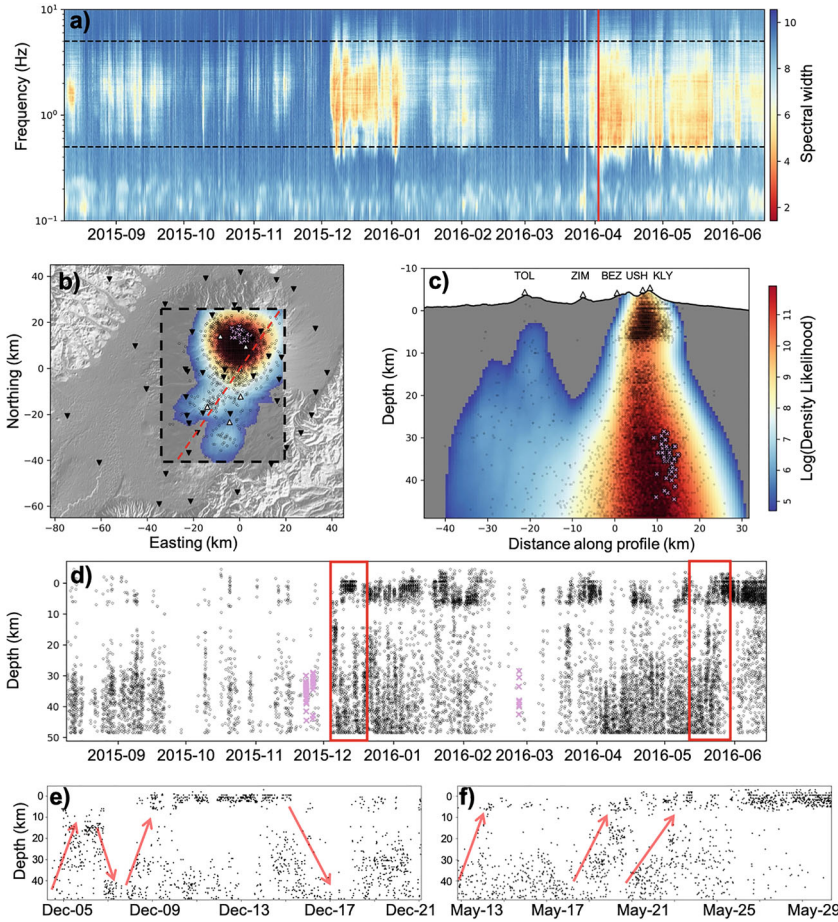


Fig. 13 Application example of tremors analysis within a transcrustal magmatic system, KVG, Kamchatka, Russia. Modified from Journeau et al. (2022). **a** Covariance matrix spectral width (20) computed for every frequency in 1200 s long overlapping windows. The two horizontal dashed black lines indicate the frequency band where most of KVG volcanic tremors are observed: 0.5–5 Hz. Red vertical line shows the onset of the Klyuchevskoy eruption on 2016-04-06. **b–c** Spatial density of the tremor sources with tremor hypocenters represented as black open circles. **b** Sum along vertical lines projected on the horizontal plane. Seismic stations are shown with black inverted triangles

and volcanoes with white triangles. Black dashed rectangle indicates limits of the area used in the grid search. **c** Sum along horizontal lines with fixed depths and along-profile distances projected on a vertical plane corresponding to the profile shown in (b) as a red dashed line. **d** Tremor depth as function of time. Light magenta crosses in (b)–(d) show the DLP swarms that occurred on 23 November 2015, 26 November 2015, and 25 February 2016. **e** and **f** Detailed view on depth-time tremor patterns during periods indicated with red rectangles in (d). Red arrows represent visually identified upward and downward migration episodes

during a few months. This average migration rate of ~ 1 km/day corresponds to an average conduit diffusivity of $\sim 100m^2s^{-1}$. The much faster migration of tremor sources (up to 10 km/h) reported by Journeau et al. (2022) can arise on top of slower diffusion processes as “pressure waves” in a system with pressure-dependent permeability (Rice 1992).

Fluid pressure transport with a variable permeability can be modeled as a conduit with multiple low permeability barriers that act as valves (e.g., Honda and Yomogida 1993; Shapiro et al. 2018) that open and close under certain thresholds. Such behavior can result from the long and heterogeneous process of formation of the transcrustal volcano-plumbing systems that are built

by multiple episodes of magmatic intrusions and remobilizations (e.g., Annen et al. 2005; Cashman et al. 2017), resulting in a strong compositional and mechanical heterogeneity where transport properties are likely to be highly variable in both space and time. In such a system, the overall permeability is proportional to the number of open versus closed valves, which, on average, increases with overall pressure gradient across the system. Closely located valves can interact, which results in cascades forming very rapidly migrating pressure transients (analogous to nonlinear pressure waves) able to propagate in both upward and downward directions (Farge et al. 2021), similar to what we observe for the KVG tremors. The modeling shows that in a conduit with background diffusivity of $\sim 100\text{m}^2\text{s}^{-1}$, the cascades of opening and closing valves can migrate with velocities up to $\sim 10\text{ km/h}$, which is close to the observations presented here.

This example from KVG shows that analysis of tremors based on seismic networks with appropriate coverage and density can be used to delineate the active parts of volcano-plumbing systems and to follow their hydrodynamic evolution in time. Note that the accuracy and resolution of the tremor spatial likelihood is limited by the knowledge of the wave propagation speed in the medium and the number of sensors forming the seismic network used in the analysis. In addition, the aperture of the network must be wide enough to allow imaging of the deepest parts of the system.

8 Some Conclusive Remarks and Perspectives

In this chapter, we argued in favor of analysing seismo-volcanic tremors with network-based methods and we described a general framework for such methods based on the network covariance matrix introduced in Sect. 6.1. Such analyzes have many advantages compared to single-station methods, because they result in much better characterisation of properties of tremor wavefields and sources and, in particular, of their locations. In the past, the network-based analysis could be considered as too heavy

and sophisticated for a routine application in volcano observatories. Also, many observatories could operate only relatively small numbers of seismometers. But this situation is rapidly changing with the development of modern instrumentation and of information and communication technologies, making the application of network-based methods much more “affordable”. So far, such key steps of the analysis including the estimation of the network covariance matrix and its eigenvalue-eigenvector decomposition (Sect. 6.1), the calculation of the spectral width for the tremor detection (Sect. 6.5), and the analysis of the eigenvectors for the tremor source location (Sect. 6.7) are today available as parts of the open-source Python library CovSeisNet (<https://covseisnet.gricad-pages.univ-grenoble-alpes.fr/covseisnet>). Running this analysis for a network composed of a few tens of seismometers does not require extensive computing resources, implying that it can be done in nearly real time in many modern volcano observatories.

Methods of the network-based analysis of seismic tremors will continue to be developed and improved. Among many possible directions for this, we can suggest a combination of network-based and polarization analyses. This implies to compute and to analyze covariances between all possible components at all stations of a network. Analysis of tremors excited by simultaneously acting sources should be further pursued. This would require to analyze in more details the eigenvalues and eigenvectors of the network covariance matrix. So far, we presented in Sects. 6.6 and 6.7 the analysis based on a single dominant eigenvector. This implicitly assumes a single dominant tremor source. In the case of multiple sources, this might be necessary to analyze more than one eigenvector and to use them together with their respective eigenvalues in order to separate different sources.

Another very important direction is combining the network-based analysis with ML. Up to present, most of attempts to apply ML algorithms to seismo-volcanic tremors have been based on single-station records or in combining “single-station” based signal features from a few seismometers. The example shown here in Sect. 6.6

illustrates how different signals/sources can be clustered based directly on a “network-based” representation of the wavefield (the dominant eigenvector of the network covariance matrix has been used in this case). Considering the very strong sensitivity of the inter-station cross-correlations to the properties of the tremor sources (Sect. 5), further developing fully network-based ML approaches might be very interesting.

In this chapter mostly aimed at describing the seismological analysis, we did not provide a detailed review of various physical models that have been suggested to explain the origin of seismic tremors. At the same time, in the two examples shown at the end of the chapter, we tried to illustrate how the network-based analysis can be used to measure properties of the tremors such as time variable spectral content or spatial source location. Those can, in turn, be used to test the hypotheses about the physical origin of tremors. The same two examples illustrate the complexity of the seismo-volcanic tremors that is related to the complex behavior of volcanic systems prior to or during eruptions. This aspect is very important to emphasize to avoid simplifying tremors just as a class (or a set of classes) of signals and to be cautious with their simplistic empirical interpretations. Instead, the tremors should be considered as a seismic manifestation of a non-stationary unfolding of several simultaneous and possibly interacting processes occurring within volcanoes. The final goal of the tremor analysis is to make inferences about these processes. To advance in this direction, many different tremor episodes should be analyzed in possible details and inter-compared. The network-based methods will be one of the key tools for such extended analysis of tremors.

Acknowledgements The development of some methods and research results presented in this chapter was supported by the European Research Council (ERC) under the European Union Horizon 2020 Research and Innovation Programme (grant agreement 787399-SEISMAZE). J. Soubestre benefited from the IS-Tremor project provided by Icelandic Research Fund, Rannis (<https://www.rannis.is/>) (contract number 217738-051).

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Coda Wave Interferometry for Volcano Monitoring

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Abstract

Coda Wave Interferometry is an increasingly popular seismic method based on ambient noise correlation functions or seismic multiplets. Its ability to detect subtle changes in the seismic velocity and structure of a medium makes it a useful tool to complement classical approaches of monitoring volcanoes. Yet, obtaining robust results and reliable interpretations requires understanding the theoretical background and assumptions of Coda Wave Interferometry, the relevant data processing and how they relate to the physical processes that can produce perturbations within a volcano. This chapter aims at expounding basic notions in this field to volcano seismologists and observers in charge of volcano monitoring. We start with the extraction of Green functions by ambient noise correlation, the description of seismic noise sources, and the propagation of coda

waves in scattering media. We then present the different techniques for calculating cross-correlation functions and detecting seismic multiplets, including the quality control procedures, as well as the main methods for estimating velocity variations and for locating the perturbations. We review the most common processes that produce these perturbations within volcanoes: stress variations, effects of hydrothermal fluids, meteorological phenomena, rock damaging and softening. Finally, we lay out some perspectives and research directions on theoretical aspects, instrumentation, data processing, applications to volcano monitoring, and physical processes that produce velocity changes and decorrelation.

Acronyms

AVV	Apparent velocity variation
CCF	Cross-correlation function
NCF	Noise correlation function
CWI	Coda wave interferometry
DC	Decorrelation
GF	Green function
HF	High frequency
MWCS	Moving window cross-spectrum
SNR	Signal-to-noise ratio

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1 Introduction

Seismology is the backbone of any volcano monitoring strategy. Volcano observatories mainly monitor earthquakes ranging from brittle failure to resonance of fluid-filled cavities and cracks. In the last two decades, new methodologies building on continuous recordings have emerged due to increased storage and computing capabilities. Among them, seismic interferometry has been extensively explored to improve volcano monitoring and can complement traditional seismic monitoring (Thelen et al. 2022). Interferometry consists of superimposing or comparing similar waves in order to extract information from their tiny differences. In seismic interferometry, the seismograms to compare are either seismic multiplets or correlation functions of ambient seismic noise. Better sensitivity to small changes in the medium is obtained when processing coda waveforms, which sample large volumes, than using ballistic waves, i.e. waves travelling directly from the source to the receiver. This is why this method is called ‘Coda Wave Interferometry’.

Due to subsurface inhomogeneity, volcanoes are highly scattering media and therefore ideal to apply methodologies based on multiply scattered waves. Aki (1957) was the first researcher to show how to extract local velocity structures from ambient seismic noise. Seismic interferometry has been introduced by Poupinet et al. (1984) who, by analysing seismic doublets, detected small velocity changes in the Earth’s crust in California (USA) associated with a tectonic earthquake. Using a similar approach, Ratdompurbo and Poupinet (1995) analysed seismic multiplets recorded at Merapi volcano (Indonesia) and observed a velocity increase before an eruption. Lobkis and Weaver (2001) developed theoretical arguments and carried out ultrasonic experiments in a laboratory to demonstrate that Green functions can be extracted from correlation functions of diffuse wave fields. Campillo and Paul (2003) and Shapiro and Campillo (2004) extended this discovery in seismology and showed that Green functions

of surface waves can be obtained using coda waves of distant earthquakes and ambient seismic noise, respectively. The extraction of Rayleigh waves by noise correlation was applied in tomographic studies in California (Shapiro et al. 2005) and at Piton de la Fournaise volcano (France; Brenguier et al. 2007). The techniques of coda wave interferometry developed first for multiplet analysis were applied to series of correlation functions of noise recorded at Merapi volcano (Sens-Schönfelder and Wegler 2006) and then in a ground-breaking study at Piton de la Fournaise that detected velocity decreases preceding eruptions (Brenguier et al. 2008).

Owing to its potential to detect small and aseismic changes in the Earth’s structure, seismic interferometry has been applied on various volcanoes and is currently used to monitor several volcanic edifices worldwide (Duputel et al. 2009; Lecocq et al. 2014). Although the first applications of the method were based on correlation of noise recorded by pairs of stations, most recent results have highlighted great performance using single stations (De Plaen et al. 2016, 2019; Machacca et al. 2019). Yet, an important issue concerns the wide variety of data processing schemes that complicates the comparison between the different studies. In addition, characterizing the noise sources and their variations through time is a pre-requisite that challenges its applications. Besides, a few years of background results are generally recommended to identify changes related to volcanic processes because seismic velocity can be sensitive to meteorological conditions.

This chapter aims at presenting a general overview of coda wave interferometry (CWI) monitoring at volcanoes. After reviewing the theoretical background of the seismic ambient noise cross-correlation method, we describe the sources of seismic noise and the main features of the coda waves. Then, we present the most common approaches to calculate the cross-correlation functions of noise records, to detect seismic multiplets, to estimate time series of velocity variations, and to locate the velocity and structural perturbations in the horizontal plane and

at depth. We insist on the importance of adapting the data processing scheme to encompass the variety of volcanic settings, network configurations and volcano seismic sources. We proceed with a discussion on the main physical processes that can modify the travel-time and path of seismic waves. These phenomena can be associated with stress variations, rock ruptures and damaging, or to the presence of magmatic and hydrothermal fluids within the edifice. The Green functions retrieved by seismic noise correlation have been extensively used for surface waves tomography of volcanoes (Spica et al. 2015; Mordret et al. 2015; Koulakov et al. 2016). However, this important topic would require long developments and is thus beyond the scope of this chapter. We finally reflect on the perspectives offered by the increasingly popular methodology of CWI in volcanology.

2 Basic Notions

In this section, we present an overview of the theoretical foundations of the techniques of ambient seismic noise cross-correlation, detection of seismic multiplets and coda wave interferometry. For more detailed discussion on these topics, the reader is invited to refer to the references listed below.

2.1 Theoretical Background

Many natural phenomena and human activities constantly apply varying forces on the solid Earth, which generates ground movements called ‘seismic ambient noise’. At short-periods (0.1–1 s), the noise is mainly produced by human activities (car traffic, machinery...) and by the interaction of the wind with the Earth’s surface. The pressure fluctuations generated by oceanic waves on the ocean bottom are the source of seismic noise at intermediate periods (1–30 s) called ‘microseisms’. Its spectrum is dominated by peaks at 14 s (primary microseism) and 7 s (secondary microseism). At long

periods (>50 s), the noise is associated to the excitation by ocean swell and storms of coupled resonances of the solid Earth and the atmosphere (Ardhuin et al. 2019). This makes any particle in the Earth move permanently with amplitudes that depend on the position, the time and the frequency. When recorded, these motions seem to be aleatory and unpredictable. However, this quasi-random wavefield contains valuable information on its sources and on the propagation medium. Aki (1957) was the first researcher to propose an approach to extract dispersion curves of surface waves by calculating correlation functions of noise recorded at several seismic stations. His method is now called Spatial Auto Correlation or SPAC and is widely used to study shallow structure on volcanoes and elsewhere (Lesage et al. 2018b). Works in helioseismology (Duvall et al. 1993) and in acoustics (Weaver and Lobkis 2001) have demonstrated that the impulse response of the medium, i.e., the Green function (GF), can be extracted from the cross-correlation functions of ambient noise. Similar approach was first applied in seismology by Campillo and Paul (2003) and Shapiro and Campillo (2004) to extract GFs between distant stations by cross-correlating records of earthquake codas or seismic noise.

The GF between two sites is equivalent to the seismogram obtained at one station when a short (Dirac) impulse is produced at the other station. A real seismogram can be considered as the convolution product of a GF, a source time function and an instrument response, plus additional noise. Many theoretical arguments and experiments have demonstrated that the GF can be approximately retrieved by the time averaged cross-correlation of ambient noise. More precisely, the relationship is:

$$\frac{d}{d\tau} C(x_A, x_B, \tau) \propto G(x_A, x_B, \tau) - G(x_A, x_B, -\tau) \quad (1)$$

where x_A and x_B are the positions of the stations, $G(x_A, x_B, \tau)$ is the Green function between the stations and $C(x_A, x_B, \tau)$ is the cross-correlation function of the seismic noise $v(x_A, t)$ and $v(x_B, t)$ recorded at the stations:

$$C(x_A, x_B, \tau) = \lim_{T \rightarrow \infty} \int_{-T}^T v(x_A, t) \cdot v(x_B, t + \tau) dt \quad (2)$$

Equation 1 is the fundamental relation of ambient noise seismology. It has been justified by many theoretical approaches: the normal modes summation (Lobkis and Weaver 2001), the theory of stationary phase (Snieder 2004; Roux et al. 2005; Lin et al. 2008), the time reversal invariance (Derode et al. 2003a,b), the use of the representation theorem (Wapenaar 2004; Wapenaar and Fokkema 2006) or the Ward identity (Snieder 2007; Weaver 2008; Froment 2011), as well as by numerical experiments (Cupillard and Capdeville 2010). Most of these theories rely on the assumption that the noise wavefield is equipartitioned and thus that all the propagation modes have similar energy and are uncorrelated (Hennino et al. 2001). This requirement is fulfilled in one or both of the following situations:

- The ambient noise is generated by homogeneously distributed and independent sources,
- The propagation medium is highly heterogeneous and the many scatterers it contains act as multiple secondary sources.

In real applications, the energy equipartition is generally not obtained, which can be due, for example, to the dominant amplitude of the fundamental mode of surface waves. In this case, or when the time series of noise used to calculate the correlation function is too short, the derivative of the noise correlation function (NCF) is only an approximation of the Green function, it can contain spurious arrivals or precursory noise (arrivals before P-wave travel time), and it can be affected by a lack of body waves or by errors in travel times, amplitudes and waveforms (Fichtner and Tsai 2019). Figure 1 displays an example of seismic noise correlation function. Several techniques of pre- and post-processing have been proposed to improve the NCFs. They are described in Sect. 3.1.

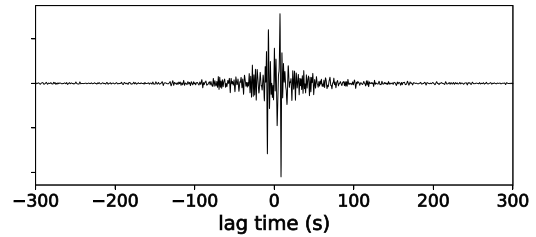


Fig. 1 Ambient noise cross-correlation function between two short-period stations at Mt Ruapehu, New Zealand. Distance between stations ~26 km, duration of stack 5 years, frequency band 0.1–5 Hz

Yet, in many cases, time-lapse monitoring can be carried out with some reliability, even when the Green functions are not well recovered from the NCF. The condition for this is a good stability of the spectral content and of the distribution of the noise sources (Hadziioannou et al. 2009). In volcanology, the very heterogeneous structure of the volcanoes tends to improve the energy equipartition. Furthermore, the high density of scatterers they contain acts as multiple secondary sources of noise. This situation is propitious for using coda wave interferometry to monitor volcanoes.

2.2 Sources of Noise

The ambient seismic noise is a permanent ground motion observed over a broad range of frequencies. It is generated by various physical mechanisms that acts as sources of seismic waves. At high frequency (HF, 1 to more than 10 Hz), the sources are mainly associated with human activity (car traffic, train, machinery) although natural phenomena such as wind or glacier calving can also contribute to the background noise. The anthropogenic part of the HF noise usually presents temporal variations with high level during daytime and low level during nights, holidays or pandemics (Lecocq et al. 2020). At mid-period (1–30 s), the noise is dominated by microseisms which are characterized by two broad spectral peaks around 7 s and 14 s (Hasselmann 1963). The so-called

primary microseisms (~ 14 s) result from the pressure fluctuations at the ocean bottom due to the breaking and/or shoaling waves. The secondary microseisms (~ 7 s) have much higher amplitude and are associated with waves produced by the interaction of incoming and reflected swells on the coast. Microseisms propagate as surface waves over long distances inside the continents and their amplitudes are orders of magnitude higher than those of HF and long-period noise, especially close to the coasts. The level of microseisms is significantly increased during storms and cyclones and the location of the corresponding sources varies accordingly (Stehly et al. 2006). At long period (>30 s), the background noise is due to the Earth's hum associated with spheroidal oscillations of the Earth and resonance modes in the atmosphere. Its level is also affected by seasonal variations and occurrence of storms.

Other sources of seismic noise are observed in active volcanic regions. They can be related to hydrothermal activity (Kedar et al. 1998; Fujita 2008) or to magma degassing. At Kilauea volcano, Hawaii, high energy volcanic tremor was observed during years before the 2018 eruption. It was due to degassing and spattering at the surface of lava lake (Fee et al. 2010). This source was relatively stable and produced continuous tremor in the range 0.3 to 1 Hz, allowing the application of CWI studies (Donaldson et al. 2017). All the sources of noise listed above may present variations in amplitude, frequency and location, which can modify the noise correlation functions impacting the CWI process. It is thus strongly recommended to monitor the features of the noise and to verify the stability of the sources of noise (Hadzioannou et al. 2009). Section 3 on methods presents some approaches for this purpose.

2.3 Characteristics of Coda Waves

When an earthquake is recorded by a seismic station at regional distance, the seismogram displays the body waves (P and S) and the surface waves (Rayleigh and Love) which are followed

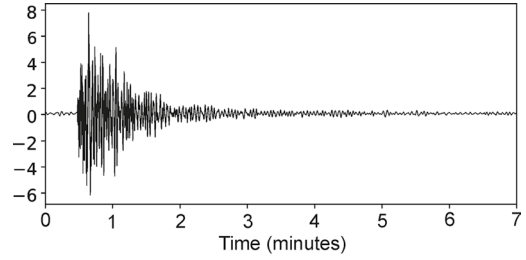


Fig. 2 M_w 4.3 earthquake occurred near Lake Taupo, New Zealand and recorded at 35 km from the epicenter. The seismogram displays a long slowly decreasing coda

by a long lasting wave train called “coda” (Fig. 2). The ray paths of the body and surface waves are included in the vertical plane that contains the hypocentre and the receiver. These waves which propagate along the shortest paths are named “ballistic waves” or sometimes “direct waves”. The coda waves are characterized by a slow and regular amplitude decrease and a duration of more than ten times the body waves travel time (Aki 1969). Aki and Chouet (1975) demonstrated that the coda waves are scattered waves on randomly distributed heterogeneities and that their power spectral can be written as:

$$P(\omega, t) = S t^{-m} \exp\left(-\frac{\omega t}{Q_c(\omega)}\right), \quad (3)$$

where S is a source term, m controls the geometrical attenuation ($m=1$ or 2 for surface and body waves, respectively), $\omega=2\pi\nu$ is the angular frequency, and Q_c is the coda quality factor that depends on the intrinsic Q_i and scattering Q_s quality factors as:

$$\frac{1}{Q_c} = \frac{1}{Q_i} + \frac{1}{Q_s}. \quad (4)$$

In a heterogeneous medium, several regimes of propagation can be observed. The type of regime depends on the relative values of several characteristic lengths: the wavelength λ , the scattering mean free path l , the transport mean free path l^* , and the absorption length l_i . l is the average distance between two scatterers, l^* is the average distance after which the incident propagation direction is lost. l and l^* are related as: $l^* = \frac{l}{(1-\langle\cos\theta\rangle)}$, where θ is the angle between

the directions of the incident and scattered wave and $\langle \rangle$ indicates the average. When the scattering is isotropic, $\langle \cos \theta \rangle = 0$ and $l = l^*$. l_i is the distance over which the wave intensity decreases by a factor e (≈ 2.73): $I \propto \exp\left(-\frac{r}{l_i}\right)$.

In the *single scattering regime*, $\lambda \ll l_i \ll l$, the waves are attenuated before encountering several scatterers (Fig. 3a). It corresponds to a propagation in a poorly heterogeneous medium and/or a strongly attenuating medium. In the *multiple scattering regime*, or *diffusion regime*, $\lambda \ll l \ll l_i$, the waves are scattered several times during their propagation between the source and the receivers and are slightly attenuated (Fig. 3b) (Dainty and Toksoz 1981). In this regime, the interaction of the waves with the scatterers produces P to S and S to P conversions, the progressive coupling between the propagation modes, and the equipartition of the energy in the phase space (Papanicolaou et al. 1996). In a heterogeneous half-space, equipartition corresponds to a S -to- P energy ratio of 7.2 (Hennino et al. 2001). This value has been measured in the coda waves of tectonic

earthquakes in Mexico (Hennino et al. 2001), which demonstrates that the coda waves in the Earth's crust are equipartitioned and thus are in the multi-scattered regime. Because volcanoes are more heterogeneous than the crust, the coda waves in volcanic structures can also be considered as multi-scattered waves.

The assumption of multi-scattering can be verified a posteriori by estimating the absorption length and the transport mean free path of the propagation medium. Using the solution of the diffusion equation, Dainty and Toksoz (1981) obtained a description of the seismic energy density in the coda as a function of time t and source-station distance r :

$$W(r, t) = \frac{E_0}{(4\pi Dt)^{\frac{p}{2}}} \cdot \exp\left(-\frac{r^2}{4Dt} - bt\right), \quad (5)$$

where E_0 is the energy at the source, D is the coefficient of diffusion, b is the coefficient for intrinsic attenuation, and $p=3$ for body waves and $p=2$ for surface waves. Because the diffusivity and intrinsic attenuation depend on the frequency, they must be estimated in various frequency bands (Wegler and Lühr 2001). Many studies have demonstrated that the coda is mainly composed of shear-waves (e.g. Aki 1992; Wegler and Lühr 2001; Yamamoto and Sato 2010). Thus a value $p=3$ must be taken for the dimension. Parameters D and b are estimated by fitting the model described by Eq. 5 to the energy envelope of seismograms. The characteristic lengths are given by $l_i = \frac{v_s}{b}$ and $l = \frac{3D}{v_s}$; their values depend thus on the S-wave velocity v_s used for the calculation. The corresponding quality factors, Q_i and Q_s for the intrinsic and scattering attenuation, respectively, are obtained by $Q_i = \frac{\omega}{b}$ and $Q_s = \frac{\omega p D}{v_s^2}$, where ω is the angular frequency.

Obermann et al. (2014b) proposed an alternative approach to estimate the scattering mean free path. Their method used data from dense arrays of seismometers and is based on the calculation of the spatial phase decoherence which is free from absorption effects.

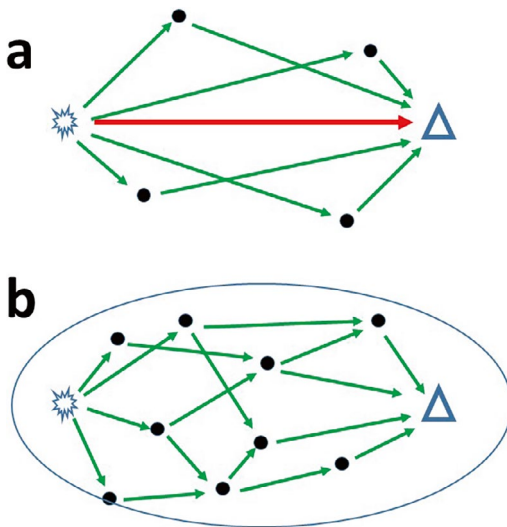


Fig. 3 Scattered waves. **a** Path of ballistic waves (red) and paths of single scattered waves (green). **b** Paths of multiple scattered waves. Coda waves travel inside an ellipsoid whose foci are the two receivers

Table 1 Characteristic lengths and miscellaneous features of propagation media estimated at several volcanoes: scattering mean free path (l), absorption length (l_i), frequency range and S-wave velocity used for the calculation, coefficient of diffusion (D), intrinsic quality factor (Q_i)

Volcano	l	l_i	Frequency range	S-wave velocity	References	Remark
	(m)	(km)	(Hz)	(km/s)		
Merapi	100		4–20	1.4	Wegler and Lühr (2001)	
Merapi	250				Parsiegla and Wegler (2008)	Layer thickness = 1.7 km
Vesuvius	200		2–16	1.5	Wegler (2003)	$D=0,1 \text{ km}^2/\text{s}$. Layer thickness = 1.5 km
Sakurajima	1600		0.5–4		Hirose et al. (2019)	$Q_i = 110$
Asama	1210		8–16	1.7	Yamamoto and Sato (2010)	Radiative transfer theory
Asama	800	4	4–20	1.5	Prudencio et al. (2017b)	
Usu	1000	7	4–20	2.8	Prudencio et al. (2017a)	$D=0.93 \text{ km}^2/\text{s}$
Tenerife	4000	10–14	6–12	3.6	Prudencio et al. (2013a)	Depth of layer = 12 km
Deception	950	5	4–20	2.8	Prudencio et al. (2013b)	
Stromboli	200	20	4–16	2.8	Prudencio et al. (2015)	$D=0.19 \text{ km}^2/\text{s}$
Auvergne	100		30		Obermann et al. (2014a, b)	Spatial phase decoherence

Table 1 summarizes the estimations of l and l_i obtained by several authors on volcanoes. The transport mean free path is generally of a few hundreds of meters, several orders of magnitude smaller than in the Earth's crust. When estimated, the absorption length is of the order of several kilometres and thus the condition of multiple scattering $l < l_i$ is fulfilled. The largest estimated values of l generally correspond to cases where the source-receiver distances are the largest and thus where the seismic waves propagate in deeper parts of the structure. This observation is consistent with a strong increase of the mean free path with depth. For example, Wegler (2003) and Parsiegla and Wegler (2008) found values of about 200 m for coda waves propagating in layers 1.5–1.7 km thick in Vesuvius and Merapi volcanoes, while Prudencio et al. (2013a, b) obtained $l \sim 4000$ m at Tenerife in a 12-km-thick layer.

3 Methods

3.1 Calculation of Cross-Correlation Functions

3.1.1 Basic Methods

The cross-correlation functions (CCFs) of signals of finite length can be computed in the time domain:

$$C_{AB}(\tau) = \frac{1}{2T} \int_{-T}^T v(x_A, t) \cdot v(x_B, t + \tau) dt \quad (6)$$

or, more efficiently, in the frequency domain:

$$C_{AB}(\omega) = V(x_A, \omega) \cdot V^*(x_B, \omega) \quad (7)$$

where $C_{AB}(\tau)$ is the time-averaged cross-correlation of the wavefield at two locations x_A and x_B , $C_{AB}(\omega)$ is the corresponding cross-spectrum, T is

the length of time integration, τ is the time lag, v is the ground velocity, V its Fourier transform, t the time, ω the angular frequency, and $*$ denotes complex conjugate (Snieder and Wapenaar 2010). In order to improve the convergence and quality of the CCFs and to retrieve reliable velocity variations, it is important to carry out some signal processing operations prior to cross-correlation (Bensen et al. 2007). The correction of the instrument response is recommended when the network includes several types of seismometer or when some instruments change during the survey. Otherwise, instrumental correction is not mandatory for monitoring by seismic interferometry.

Windsorizing (i.e. amplitude normalization) (Tukey 1962) is generally applied to decrease the influence of discrete signals such as earthquakes. It can involve performing the 1-bit normalization (i.e., keeping the sign only) (Larose 2004), clipping the record to a multiple of the root mean square (Sabra et al. 2005), dividing the signal by its envelope (Zhan et al. 2013) or by the running absolute mean values (Bensen et al. 2007; Ritswoller and Feng 2019). Besides periods of intense earthquake activity (Woods et al. 2018), the factor used for clipping does not dramatically impact the results for monitoring purpose (Caudron et al. 2022). Bensen et al. (2007) compare five methods of amplitude normalization. They obtain the best results when using the 1 bit and the running absolute mean normalizations and they prefer the later method for its greater flexibility and adaptability to the data.

Ambient noise is not flat (i.e., not white) in the frequency domain. Spectral whitening is generally applied to set the amplitude of the signal spectrum to 1 for all frequencies and thereby decreases the influence of varying sources. It results in a broadened spectrum and mitigates degradation induced by peaked sources which are often associated with volcanic activity.

The choice of the frequency band is also critical in seismic interferometry. Scientists should first carefully verify that the selected frequencies contain sufficient energy and produce high Signal-to-Noise Ratio (SNR) NCFs. They could

for example compute power spectral densities of each seismic trace (Caudron et al. 2021). In addition, they should bear in mind the depth-frequency dependence; high frequencies typically allowing to probe the shallow subsurface.

An alternative to classical cross correlation is the Phase Cross Correlation (PCC) that measures the similarity of the instantaneous phase of the analytical traces (Schimmel 1999). It removes the need for temporal and spectral normalization before cross-correlation but has not been used extensively in volcano seismology (De Plaen et al. 2019; Sánchez-Pastor et al. 2018).

3.1.2 Convergence, Quality Control

The theoretical conditions for extracting GFs by noise correlation (azimuthally homogeneous distribution of sources, energy equipartition) are not totally fulfilled in real cases (see Sect. 2.1). As a consequence, only approximations of GFs can be obtained from noise records. Furthermore, the NCFs are generally not symmetrical and they can include precursory noise at time lags smaller than the travel times of ballistic waves between the two stations. Reconstructing the GFs, however, is not a necessary requirement for noise-based monitoring. Instead, the main condition is the relative stability of the background noise structure (Hadzioannou et al. 2009).

Effective monitoring of subtle changes depends on our ability to make accurate and repeatable measurements on near identical waveforms. Hence, NCFs should have highly similar coda. It is thus necessary to verify that the convergence of the NCFs towards a stable function is good enough and that the NCFs are similar through time. Several techniques and quality criteria can be used for this purpose.

The most common method to enhance coherent energy in the signal and to reduce incoherent energy is the stacking of a series of NCFs $C_{ABi}(\tau)$. This process takes the general form:

$$C_{AB}(\tau) = \sum_{i=1}^N C_{ABi}(\tau) \cdot w_i \quad (8)$$

where w_i are weights. The choice of N results from a trade-off between the quality of convergence and the temporal resolution. This time resolution is equal to the total duration NT of the N segments of noise, each of length T , used for the stack. A Signal-to-Noise-Ratio (SNR) can be defined to characterize the NCFs. One definition uses the maximum of amplitude of ballistic waves divided by the root-mean-square of the trailing noise (i.e. the signals after the end of the coda). It is unclear, however, how appropriate this SNR measure is for evaluating the stability of the coda. An alternative approach defines the SNR as a function of time lag (Larose et al. 2007; Clarke et al. 2011). The level of signal $s(\tau)$ is given by the amplitude envelope of the NCF following:

$$s(\tau) = [C_{AB}(\tau) + iH(C_{AB}(\tau))] \quad (9)$$

where $H(\cdot)$ denotes the Hilbert transform and i is the imaginary unit. The level of noise $\sigma(\tau)$ is determined as the amplitude of residual fluctuations between each constituent $C_{ABi}(\tau)$ of the NCF following:

$$\sigma(\tau) = \sqrt{\frac{\langle C_{AB}(\tau)^2 \rangle - \langle C_{AB}(\tau) \rangle^2}{N-1}} \quad (10)$$

where $\langle \cdot \rangle$ denotes the average over N sub-NCFs. The SNR is then estimated as:

$$SNR(\tau) = \frac{\overline{s(\tau)}}{\overline{\sigma(\tau)}} \quad (11)$$

where the overlines indicate smoothing. A single value for a given NCF can be obtained by computing an average within the coda. As a rule-of-thumb, the SNR (using either definition) is approximately proportional to the square root of the duration of the noise record: $SNR \propto \sqrt{NT}$ (Fig. 4). NT is also the sampling interval of the velocity variations that will be calculated from the stacked NCFs. It should be small enough in order to be able to observe rapid volcanic phenomena while the corresponding SNR should be high enough to ensure a suitable level of convergence.

The quality and stability of NCFs can be assessed by visual inspection of the corresponding spectrograms and correlograms, where coherent and similar arrivals are easy to identify and changes in waveform or in frequency content can be detected. The correlation matrix built with the cross-correlation coefficients between all the pairs of NCFs provides similar

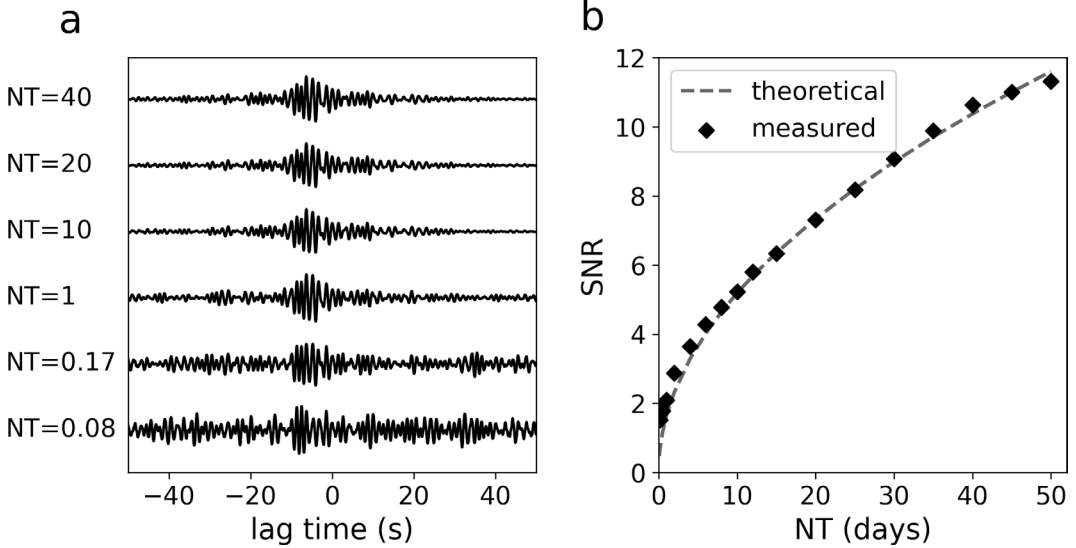


Fig. 4 NCF convergence with increasing duration of noise records NT . **a** Stacked NCFs for a pair of stations at Piton de la Fournaise volcano (La Réunion, France).

b Average SNR measured between ± 10 – 40 s lag time following Eq. 11. The theoretical curve is of the form $\alpha\sqrt{NT}$ where α is the fit coefficient

information. The similarity between individual NCFs and the reference NCF (usually the average of all the NCFs) can also be measured by their correlation coefficients or by their coherency. Alternatively, hierarchical clustering of a dissimilarity matrix based on the correlation coefficients between individual NCFs has shown promise towards identifying structure in volcanic datasets (Yates et al. 2023).

Many techniques have been proposed to improve the quality of the NCFs. In the stacking process (Eq. 8), the weights w_i can be equal to one (giving the linear stack) or some of them can be set to a smaller value or to zero to exclude low quality or contaminated noise segments (Baig et al. 2009; Liu et al. 2016). An extension of the Welch's method (Welch 1967) allows a faster convergence towards the GF. It consists of using short duration overlapped segments of noise rather than long windows (Seats et al. 2012). Several studies, still not applied much in volcano monitoring, have proposed to de-noise the NCFs using algorithms designed to enhance coherent parts of the signals. They include filters based on the S-transform (Baig et al. 2009; Hadziioannou et al. 2011) or the curvelet transform (Stehly et al. 2015), the singular-value-decomposition-based Wiener filter (Moreau et al. 2017; Machacca et al. 2019), and the covariance matrix eigenspectrum (Seydoux et al. 2017). All these approaches can help improve the SNR and the velocity of convergence, resulting in better time resolution and enhanced ability in detecting small changes in the medium for monitoring applications.

Finally, to respect causality, NCFs should be dated as the end time of the corresponding noise records used in stacking. Because the amplitude of coda waves exponentially decreases, the end of the coda can be estimated by plotting the logarithm of the envelop as a function of time and by determining the end of the decreasing linear trend (e.g., Donaldson et al. 2017). Alternatively, measures of SNR against -time lag (e.g. Eq. 11) can aid in selecting a suitable coda window.

The data processing and quality control discussed in this section and the detection of medium perturbations described in the

subsequent sections can be carried on the causal and acausal sides of the NCFs, as well as on their average. No general rules exist because it mainly depends on the spatial distribution and stability of the noise sources. We suggest to process both sides of the NCFs separately, to assess their convergence and quality, and to calculate the corresponding velocity variations and decorrelations. Similar results obtained with both sides of the correlation functions would indicate good reliability. Otherwise, it is advisable to process only the side that presents the greatest SNR.

3.1.3 Case of Single Station

Many volcanoes are only monitored by one or a few seismometers, especially in remote locations (Caudron et al. 2015; Bennington et al. 2018). Building on studies in non-volcanic areas (Hobiger et al. 2014), much work has been devoted to explore the potential of the so-called single station approach to estimate seismic velocity changes at volcanoes (De Plaen et al. 2016; Machacca et al. 2019). The processing of data from a single station is easier than for a pair of stations. Furthermore, the medium sampled by the coda waves of cross-components correlation function is centred on the station and thus has a different shape than that of a station pair (see Sect. 3.4.2 on sensitivity kernels), producing complementary information. Additionally, it allows extracting dv/v at higher frequencies, hence shallower depths (~100s of meters), than the station pair approach because there is less loss due to attenuation. Several strategies can be adopted. Some authors compute CCFs between all possible combinations of channels (EE, NN, ZZ, EZ, EN, NZ) (Bennington et al. 2015; Haney et al. 2014; De Plaen et al. 2016; Yukutake et al. 2016). De Plaen et al. (2016) did not use the auto correlations, because by setting the spectral amplitude of the signal to 1 for all frequencies, i.e. spectral whitening, only the phase of the signal would remain and the auto-correlation of such a signal does not contain information on the medium anymore. An alternative is to use a smoothed version of the amplitude spectrum to weigh the complex amplitude spectrum (Bensen et al. 2007). In that sense, the

whitening would consist of a spectral balancing (M. Haney, pers. com.). For the cross-component correlations, the whitening procedure can be applied. We stress that the PCC approach solves the normalization issue (Schimmel et al. 2011; De Plaen et al. 2019 and Caudron et al. 2022).

3.2 Detection and Use of Multiplets

The coda wave interferometry is based on the comparison of series of similar waveforms. Besides the use of noise correlation functions, one can use records generated by repeated active sources (Nishimura et al. 2005; Hirose et al. 2017) or multiplets of seismic events (Budi-Santoso and Lesage 2016; Hotovec-Ellis et al. 2014, 2022). A seismic doublet, respectively a multiplet, is a group of two, or more, earthquakes with identical source mechanism and location (Poupinet et al. 1984). Because their hypocentres are close to each other, the wave paths are almost the same. The resulting waveforms present a high degree of similarity including in the coda. Seismic multiplets, also called families of similar events or repeating earthquakes, are relatively common in volcanoes and can include either VT or LP events (Caplan-Auerbach and Petersen 2005; Wellik et al. 2021). Because they result from repeatable, non-destructive sources, their occurrence brings information on the physical processes involved at the source (Tuffen et al. 2003). The degree of similarity of two seismograms can be evaluated either by their correlation coefficient in the time domain (or maximum of correlation function), or by their coherency in the frequency domain which is the smoothed cross-spectrum normalized by the smoothed self-spectra (Got et al. 1994). In these calculations, the duration and position of the analysis window and the threshold of similarity must be chosen carefully. Indeed, a high threshold of similarity favours the detection of small perturbations in the medium but reduces the number of events in each family and thus the temporal sampling. As a result, there is a trade-off between the sensitivity of the

method and its resolution in time. Several strategies for identifying families of similar events can be carried out. In a first approach, an algorithm of earthquake detection, such as STA/LTA, is applied to the continuous data set. Then the correlation coefficient of each pair of events is calculated and a correlation matrix is formed for the whole data set. Finally, a clustering algorithm is used to identify all the events belonging to each family. Two events are grouped in the same family if their correlation coefficient is higher than a given threshold. Another approach consists in using master events and calculating the correlation function of these events with the complete seismic records. Each time a correlation function is higher than a given threshold, an event belonging to the same multiplet as the master event is identified. Several computer programs have been developed for this purpose. The most popular ones in volcano seismology are the Matlab correlation tools of GISMO and the Python tool REDPy (See Table 2 for references).

3.3 Volcano Monitoring by Coda Wave Interferometry

3.3.1 Theoretical Considerations and Standard Procedure for Estimating Velocity Variations

Two seismic wave trains generated by the same source, that propagate within the same medium and are recorded by the same instrument, present identical waveforms. Any change in the source location or mechanism, in the medium or in the seismic station that occurs between the occurrence of the two events will result in modifications of the second waveform with respect to the first one. Two types of perturbation can modify the medium: seismic wave velocity variations and structural changes, such as fracture aperture or dike injection.

A variation of seismic velocity produces changes in the travel time of the different seismic waves that can be detected and quantified by measuring the corresponding phase shift

Table 2 Available software for the calculation of noise correlation functions, coda wave interferometry, and detection of seismic multiplets

Software	Publication	Website
MSNoise	Lecocq, T., C. Caudron, et F. Brenguier (2014), MSNoise, a Python Package for Monitoring Seismic Velocity Changes Using Ambient Seismic Noise, <i>Seismological Research Letters</i> , 85(3), 715–726, https://doi.org/10.1785/0220130073	http://www.msnoise.org/
SeisNoise.jl	Clements, T. and Denolle, M.A., 2021. SeisNoise.jl: Ambient seismic noise cross correlation on the CPU and GPU in Julia. <i>Seismological Research Letters</i> , 92(1), 517–527	https://nextjournal.com/thclements/seisnoisejl-gpu-computing-tutorial
Cross wavelet transform	Mao, S., Mordret, A., Campillo, M., Fang, H. and van der Hilst, R.D., 2020. On the measurement of seismic traveltime changes in the time–frequency domain with wavelet cross-spectrum analysis. <i>Geophysical Journal International</i> , 221(1), 550–568	https://github.com/Qhig/cross-wavelet-transform/releases/tag/v1.0.0
PCC	Schimmel, M., 1999. Phase cross-correlations: Design, comparisons, and applications. <i>Bulletin of the Seismological Society of America</i> , 89(5), 1366–1378	https://github.com/sergiventosa/FastPCC
GISMO	Thompson, G., Reyes, C. and Kempler, L., 2017. GISMO: A MATLAB toolbox for seismic research, monitoring, & education. School of Geosciences Faculty and Staff Publications, 2183, University of South Florida	http://geoscience-community-codes.github.io/GISMO/
REDPy	Hotovec-Ellis, A.J., and Jeffries, C., 2016. Near Real-time Detection, Clustering, and Analysis of Repeating Earthquakes: Application to Mount St. Helens and Redoubt Volcanoes—Invited, presented at Seismological Society of America Annual Meeting, Reno, Nevada, 20 Apr	https://github.com/ahotovec/REDPy , https://www.usgs.gov/software/redpyrepeating-earthquake-detectortpy-python-version-100

between the waveforms. If the velocity change is uniform within the medium, the relative variation of the travel time is equal to the opposite of the relative velocity variation: $\frac{\delta t}{t} = -\frac{\delta v}{v}$. In this case, the absolute value of the phase shift δt increases linearly with the travel time t . In most real cases, the velocity variation is not uniform and varies in space. The observed relative variation of the phase shift is thus no more equal to the relative velocity variation and the phase shift is no more a linear function of the travel time. This is why several authors call the measured relative variation of travel time ‘Apparent Velocity Variation’ (AVV): $-\frac{\delta t}{t} = \text{AVV}(t) \neq \frac{\delta v}{v}$.

The absolute value of the time shift is theoretically larger in the coda waves than in the ballistic waves (body and surface waves) and

is therefore more convenient to estimate in the coda. The coda waves are mainly multi-scattered waves that travel inside an ellipsoidal volume whose foci are the source and receiver positions. This volume increases with increasing travel times. In contrast to the ballistic waves that travel in the vertical plane that includes the source and the receiver, the coda waves propagate in a random walk manner (Pacheco and Snieder 2005). They can go one or several times through the regions of the medium where the perturbations occur and that are outside the direct path between the source and the receiver. The coda waves are thus much more sensitive to changes in the medium.

In the coda, the measured relative velocity variation is a weighted average of the relative

variations of the P-wave (α) and of the S-wave (β) velocities (Snieder 2002, 2006):

$$\frac{\delta v}{v} = \frac{\beta^3}{2\alpha^3 + \beta^3} \frac{\delta \alpha}{\alpha} + \frac{2\alpha^3}{2\alpha^3 + \beta^3} \frac{\delta \beta}{\beta}. \quad (12)$$

Thus for a Poisson medium where $\alpha = \sqrt{3}\beta$:

$$\frac{\delta v}{v} = 0.088 \frac{\delta \alpha}{\alpha} + 0.912 \frac{\delta \beta}{\beta}. \quad (13)$$

These relations show that the observed velocity variations depend mainly on the changes in the shear-wave velocity.

The structural changes can result from a fracture aperture, a dike or sill injection, a modification of existing scatterers, or a change in the volcano topography (e.g., lava flow, collapse). They are equivalent to the creation of new scatterers that modify the wave paths in the medium. As a consequence, the waveforms are modified, which can be evidenced by a decrease of the correlation coefficient CC that measures the degree of similarity of the waveforms. In many studies, these modifications are quantified by the decorrelation: $DC = 1 - CC$ (Larose et al. 2010; Planès 2013; Planès et al. 2014).

As discussed above, the detection of perturbations in the medium is based on the comparison of waveforms of ambient noise correlation functions or of similar events. In this process, it is important to verify that the modifications of the waveforms are not due to a source effect or to a change of instrument. In the latter case, the correction for the instrument response must be applied to avoid any bias in the comparison. When using noise correlation functions, the distribution of noise sources and their spectral content must be stable enough through time. Several techniques described in Sect. 3.1.2 can be used to improve this stability or to detect possible instabilities. For example, if the correlation coefficient between two waveforms is below a given threshold, this pair is discarded for subsequent analysis. In strongly heterogeneous medium, such as volcanic structures, the numerous scatterers act as secondary sources of noise which favours the stability of the correlation functions, even if their convergence toward the Green's functions is not complete (Fichtner

and Tsai 2019). For this reason, asymmetrical correlation functions can be used for monitoring purpose provided they are stable enough through time.

In order to obtain time series of AVV or decorrelation, we can use long-lived multiplets or NCFs computed using a moving window of the continuous seismic record. Each event of a multiplet is compared with a reference event which can be the first one or the one with the largest signal-to-noise ratio. The current NCFs are also compared to a reference NCF which is generally a NCF stacked over a long time period. The choice of this reference is important because it can have an influence on the resulting AVV or DC time series. Many authors use the NCFs stacked over the whole period of study while other choose a period of stability of the volcano. In the cases where the NCFs present large changes, several references can be used (Sens-Schönfelder et al. 2014). An alternative approach has been proposed to calculate time series of velocity variations without any reference NCF (see Box).

Box. Retrieving AVV series without reference

Instead of using an arbitrary reference NCF, Brenguier et al. (2014) proposed to calculate the relative AVV between all the pairs of NCF. Then they developed to the first order the relationships between the $N(N-1)/2$ calculated AVVs and the time series of N values of velocity change. This development relies on the assumption that the relative AVVs are small. For larger AVVs, a development to the second order can be used instead (B. Valette, personal communication). The following step consists in solving the set of relationships to estimate the time series of velocity changes. This can be considered as a classical Bayesian least-squares inverse problem. This procedure includes the introduction of a covariance matrix that describes the errors on the data—the calculated AVVs—and an a

priori covariance matrix on the model—the time series—which can take the form:

$$\text{cov}(t_i, t_j) = \sigma_v^2 \exp \left[-\frac{|t_i - t_j|}{\chi} \right], \quad (14)$$

where t_i and t_j are two dates of the time series, σ_v is the a priori error on the model, and χ is a correlation length. The results of the inversion depend on the values used for the a priori error σ_v and the correlation length (Gómez-García et al. 2018). Increasing σ_v allows larger variations of the model. χ controls the smoothing of the model, the larger the correlation length is, the smoother the model is (Fig. 5). In order to find the optimal control parameters (σ_v , χ), the method of ‘L-curve’ (Hansen 1992) can be used. It consists in testing many sets of parameters and to represent the resulting misfits as a function of the maximum of the absolute value of the estimated model. The ‘best’

parameters are associated to the closest points of the curve to the origin (Fig. 6). This approach is especially useful to process sparse data sets (Gómez-García et al. 2018), to reconstruct time series of velocity variation from poorly similar NCFs, and to generate time series with high temporal resolution (Muzellec et al. 2023).

3.3.2 Stretching

Lobkis and Weaver (2003) and Sens-Schönfelder and Wegler (2006) proposed a method to measure the time shift due to velocity variations in the medium. The current waveform is compared to the reference one and one of the two traces is stretched or compressed in time by a series of stretching factors ε which varies in a given interval—for example $\pm 2\%$. The similarity of the two waveforms u_1 and u_2 is measured by their correlation coefficient:

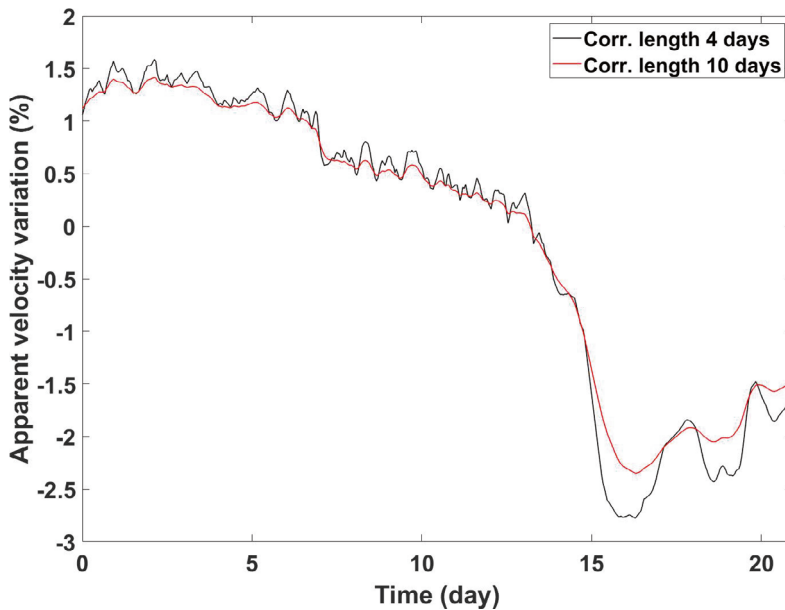
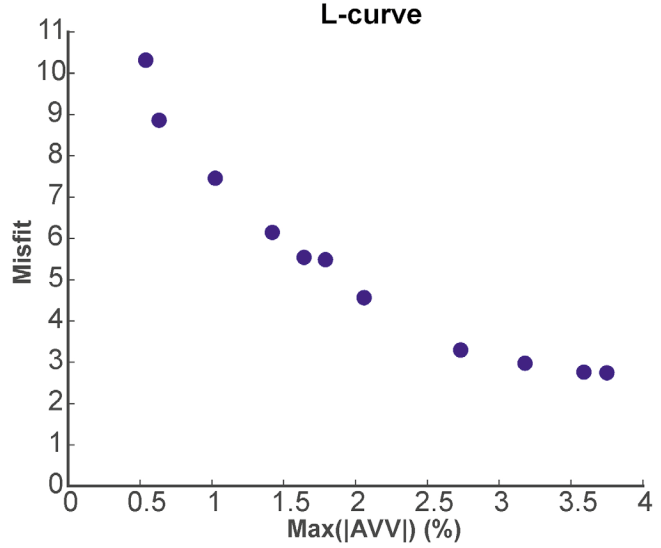


Fig. 5 Apparent velocity variations calculated without reference NCF. The correlation length for the inversion is either 4 days (black curve) or 10 days (red curve)

Fig. 6 Example of L-curve used to define the optimal inversion parameters in the calculation of AVV without reference



$$CC(\varepsilon) = \frac{\int_{t_1}^{t_2} u_1[t(1 - \varepsilon)] \cdot u_2[t] dt}{\sqrt{\int_{t_1}^{t_2} u_1^2[t] dt \cdot \int_{t_1}^{t_2} u_2^2[t] dt}} \quad (15)$$

where t_1 and t_2 are the limits of the delay window used in the coda. The stretching factor

ε_{max} that produces the largest correlation coefficient—i.e. the better similarity between the two traces—gives an estimation of the apparent velocity variation (Fig. 7).

We would like to stress that, to optimize the computational time, it is preferable to apply the stretching to the reference trace and store the traces corresponding to all the tentative

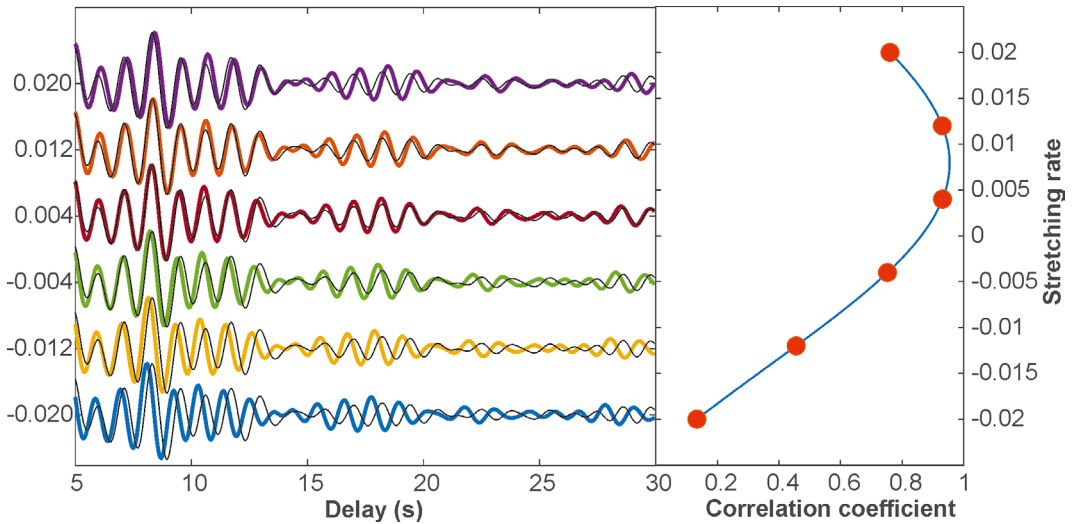


Fig. 7 Principle of the stretching method. On the left hand panel, the thin black lines correspond to the reference NCF and the color lines are the current NCF with different levels of stretching. The right hand panel

displays the correlation coefficients between the reference and the stretched NCFs. The relative velocity variation is given by the stretching rate that maximizes the correlation coefficient

stretching factors in memory. The correlation coefficients between the current waveform $u_2(t)$ and each stretched version of the reference waveform $u_1[t(1 - \varepsilon)]$ can then be calculated. In this case the estimated apparent velocity variation is $AVV = -\varepsilon_{max}$. The bounds and spacing of the grid search for ε must also be adapted to the expected amplitude of velocity change.

Weaver et al. (2011) gave an estimation of the *rms* error on the estimation of ε_{max} as:

$$rms(\varepsilon) = \frac{\sqrt{1 - CC_{max}^2}}{2CC_{max}} \sqrt{\frac{6\sqrt{\frac{\pi}{2}}T}{\omega_c^2(t_2^3 - t_1^3)}} \quad (16)$$

where CC_{max} is the maximal value of the correlation coefficient, T is the inverse of the frequency interval used, and ω_c is the central angular frequency. This

expression takes into account the effect of noise on the compared waveforms. Because the effective uncertainties are probably larger than the values obtained with Eq. 16, some authors add a constant error to the *rms* (Lesage et al. 2014).

3.3.3 Moving Window Cross-Spectral Method

The cross-spectral analysis was first introduced in seismology by Poupinet et al. (1984) for earthquake doublets. The Moving Window Cross-Spectral (MWCS) method was then proposed by Ratdomopurbo and Poupinet (1995) to estimate velocity variations at Merapi volcano from multiplets. Its first application with NCFs and CWI was carried out by Brenguier et al. (2008) at Piton de la Fournaise volcano.

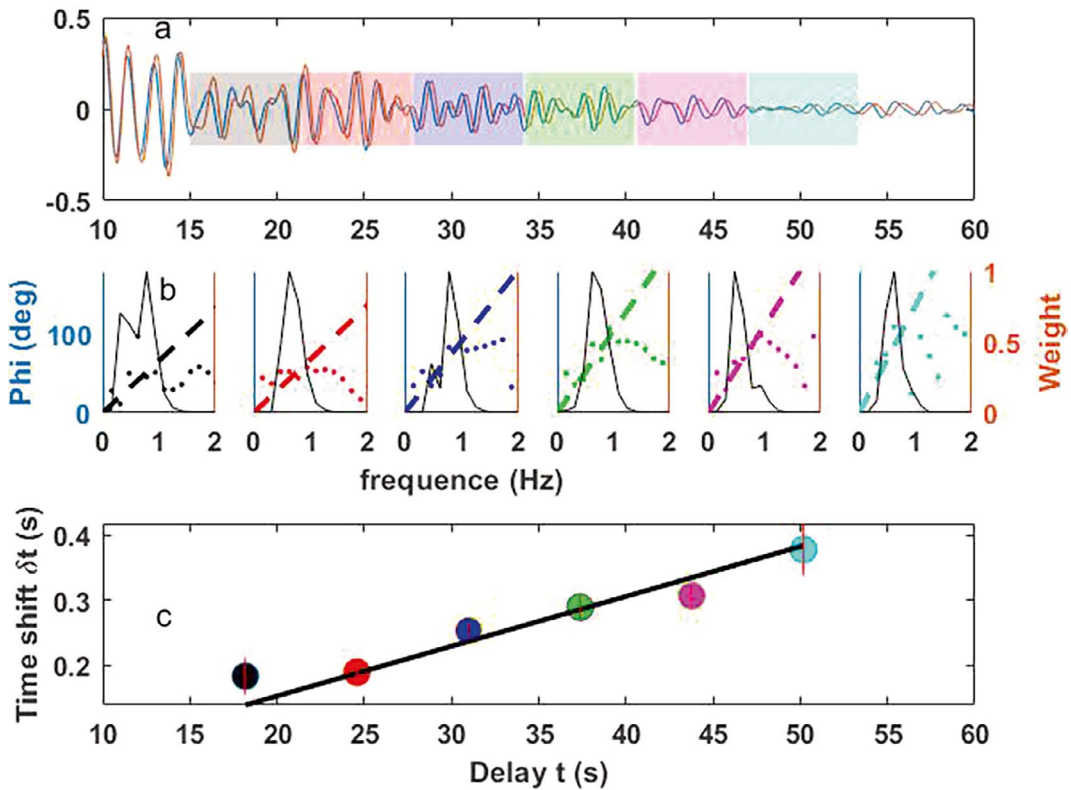


Fig. 8 Principle of the Moving Window Cross-Spectrum method. **a** Several windows are defined in the coda of two NCFs (black and red curves). **b** For each window, a weight function (black curve) is calculated from the cross-spectrum and cross-coherence between the signals. A weighted linear regression (dashed line) is carried out on the phase of the cross-spectrum (dots).

The time shift between the signal is obtained from the slope of the phase. **c** The time shifts obtained in each window (dots and error bars) are plotted as a function of the delay in the coda and a straight line is fitted by another linear regression. Its slope $\delta t/t$ is the opposite of the apparent velocity variation between the time of occurrence of the two signals

This method for estimating velocity variations consists in two steps (Fig. 8). In the first one, a series of overlapping small windows are defined at different time lags in the coda of the NCFs (Fig. 8a). These windows must contain enough samples in order to accurately measure time shifts in the frequency range of interest. Furthermore, longer time windows have been shown to reduce the influence of cycle skipping (Mikesell et al. 2015). However, the assumption of a constant time shift within each window is less likely satisfied with increasing window length. Thus, the choice of window duration is a trade-off between the accuracy of delay time measurements and the time resolution between consecutive measurements. Most studies use window lengths that are equal to (Hadziioannou et al. 2011; Taira et al. 2018) or larger than (Hillers et al. 2015a; Mordret et al. 2016) the longest period of the signal.

Then the time-shifts between the reference and the current NCFs inside each window are calculated by the cross-spectral method (Fig. 8b). In this calculation, the corresponding segments of signal are demeaned and tapered and their cross-spectrum is computed as: $X(\nu) = F_1(\nu) \cdot F_2^*(\nu) = |X(\nu)| e^{i\phi(\nu)}$, where $F_1(\nu)$ and $F_2(\nu)$ are the Fourier transforms of the reference and current NCF segments, respectively, $*$ denotes complex conjugate, $|X(\nu)|$ is the amplitude of the cross-spectrum, and $\phi(\nu)$ its phase. If the two segments have similar waveforms and are shifted in time, the unwrapped phase is linearly proportional to frequency: $\phi(\nu) = 2\pi \delta t \nu$. The time shift δt is obtained by weighted linear regression from the slope of $\phi(\nu)$ in the frequency interval where the signals are similar. The cross-coherence can be used to measure this similarity:

$$C(\nu) = \frac{\overline{|X(\nu)|}}{\sqrt{\overline{|F_1(\nu)|^2} \cdot \overline{|F_2(\nu)|^2}}} \quad (17)$$

where the overlines indicate smoothing. The weights for the regression are usually defined as (Clarke et al. 2011):

$$w(\nu) = \sqrt{\frac{C^2(\nu)}{1 - C^2(\nu)}} \cdot \sqrt{|X(\nu)|} \quad (18)$$

Errors on the slope and the time shift can also be calculated together with the linear regression (Clarke et al. 2011; Lecocq et al. 2014). Note that the error on the time shift can be much smaller than the sampling interval, which is the main advantage of the cross-spectral method with respect to the cross-correlation method.

In the second step of the method, the time shifts δt estimated in each coda segment are plotted as a function of the time lags t of the windows (Fig. 8c). Under the assumption of a homogeneous velocity perturbation in the medium, the relationship between δt and t is linear. Therefore, its slope $\delta t/t$ can be estimated by another weighted linear regression which takes the errors on δt into account allowing to estimate the uncertainties on the slope and the corresponding $AVV = -\delta t/t$ (Clarke et al. 2011; Lecocq et al. 2014).

3.3.4 Discussion on the Methods of Velocity Variation Calculation

After presenting the two most popular methods used for calculating velocity variations, some questions arise: What are the advantages and disadvantages of each method? Which method should be used according to the features of the multiplets or the NCFs to process? Several papers include a discussion to answer these questions (Obermann and Hillers 2019) and the debate is still open.

In the second step of the MWCS method, the linear relationship between the time shift δt and the time lag t relies on the assumption of a homogeneous distribution of velocity perturbation. Similar assumption is implicitly made when a long segment of coda is used for the stretching method. However, in many cases and especially in volcanoes, this assumption is not well verified, i.e. δt is not proportional to t , and the optimal stretching coefficient is not constant along the coda. To illustrate this issue, we used Eq. 20 to calculate the time shift δt produced by a point source perturbation as a function of the time lag t . Figure 9 shows that the function $\delta t(t)$ is not linear. In any case, the values of δt and $\delta t/t$ can still be estimated at various time lags with both methods by using short sections of coda.

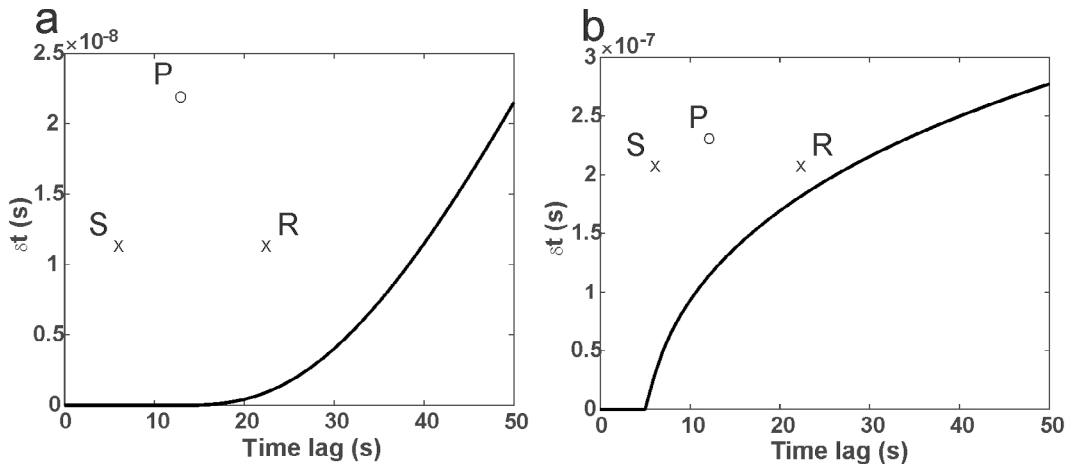


Fig. 9 Time shift δt as a function of time lag t calculated for a point source perturbation. The parameters used are the coordinates of the stations $S (x_s, y_s) = (0, 0)$ and $R (x_r, y_r) = (10, 000, 0)$ and of the source of perturbation P

(x, y) , the wave velocity $v = 2000 \text{ ms}^{-1}$ and the free mean path $l^* = 1000 \text{ m}$. Vertical scale is arbitrary. **a** $x = 4000 \text{ m}$, $y = 10,000 \text{ m}$; **b** $x = 4000 \text{ m}$, $y = 2000 \text{ m}$

The Moving Window Cross-Spectrum method and the stretching method generally produce similar results and the use of one or the other technique may result from a personal choice. The MWCS method tends to yield more stable results (Hillers et al. 2015b), especially when processing high SNR NCFs, and it can detect and correct easily clock errors of the seismic stations (Stehly et al. 2007). In some situations, mainly at high frequency, for monochromatic signals, short coda windows, and/or for large velocity variations (a few percent), the MWCS may suffer the issue of cycle skipping (James et al. 2017; Donaldson et al. 2019). The MWCS and stretching methods may generate small spurious velocity variations when the amplitude and spectral content of the noise source vary (Zhan et al. 2013; Mikesell et al. 2015; Yuan et al. 2021). However, according to Mao et al. (2020), the bias is of the order of 10^{-5} and thus negligible in most cases.

The cross-spectral analysis requires that a linear regression is performed on the cross-spectrum phase in the frequency domain. It is thus convenient to use signals with a relatively large frequency range and coda windows with long enough durations so the cross-spectrum is well-sampled. Conversely, the stretching method can process narrow band signals with duration of at

least 2 cycles. The stretching method is more stable in case of noisy NCFs (Hadziioannou et al. 2009; Donaldson et al. 2019) and can be used on shorter segments of coda. This is useful, when the AVV depends on the time lapse, to improve the estimation of location and depth of the velocity perturbations. Furthermore, it provides a value of correlation coefficient between the reference and the current NCFs after stretching and a way to detect and correct possible sampling frequency drift of the seismic stations (Lesage et al. 2014).

It is not easy to compare the computational costs of the two methods because they depend on the parameters used for the calculations (coda window length, frequency range, overlap, stretching increment and range, etc.). Some authors consider that MWCS is faster than the stretching method (Hadziioannou et al. 2009; Yuan et al. 2021; Mikesell et al. 2015). The computational time of the stretching algorithm depends on the choice of the NCF (reference or current) which is stretched. This time is strongly reduced when the reference NCF is stretched and the resulting time series are stored in memory only once for all the values of stretching coefficient and then compared to the current NCFs.

Alternative algorithms for the calculation of velocity variations have been proposed recently, such as the Dynamic Time

Warping (Mikesell et al. 2015), the Wavelet Cross-Spectrum (Mao et al. 2020), or combination of methods (Yuan et al. 2021). They can be less sensitive to noisy NCFs and provide better spectral resolution. The Wavelet Cross-Spectrum method may have a higher computational cost (Yuan et al. 2021), but it removes the need for several filters, which can save time in some cases.

3.4 Locating Velocity and Structural Perturbations

3.4.1 Introduction

It is important to locate in the structure the origin of AVV and decorrelation perturbations, i.e. to estimate the spatial distribution of the physical velocity changes and of the structural modifications. Indeed, if carried out in real-time, the location of perturbations associated with a forthcoming eruptive event, especially in case of flank eruptions, would be very helpful to manage the corresponding risks. Moreover, the detection and location of dike intrusion, pressure sources or stress field variations are important information for the study of physical processes in the magmatic or hydrothermal systems.

Brenguier et al. (2008) in their pioneering study on Piton de la Fournaise proposed a first approach to regionalize the velocity variations. They calculated the AVV for each pair of stations and assigned the obtained values to the grid cells located at less than 2 km from the direct path. The values assigned to each cell are then averaged (Brenguier et al. 2008; Duputel et al. 2009). Taking advantage of the large number of stations of the Japanese Hi-net network, Brenguier et al. (2014) calculated the average of AVV obtained for all the pairs which include a given station and assigned the result to the corresponding station site. They then interpolated the values obtained at each station to produce a map of velocity variations.

However, because the AVV are estimated by analysing coda waves, which are multiply scattered waves, it is possible to estimate their sensitivity kernels to improve the location

of the perturbations. The theoretical bases of this approach were developed by Pacheco and Snieder (2005), Planés et al. (2014) and Margerin et al. (2016), among others. As a first application, Larose et al. (2010) retrieved the position of a small hole drilled in a concrete block by inverting the decorrelation coefficients calculated between a set of transducers.

In the following sections, we summarize the theoretical background of the propagation of scattered coda waves, the calculation of sensitivity kernels, and the definition of the inverse problem to solve for locating the velocity or structural perturbations.

3.4.2 Sensitivity Kernels

When addressing the locations in a heterogeneous medium, two different cases must be distinguished. A small velocity change in the medium does not significantly modify the wave propagation paths. It produces time shifts in the seismograms and almost no change in their waveforms (Fig. 10a). It is called ‘passive perturbation’. A modification in the medium, such as the aperture of a crack or a dike, introduces a new scatter and produces new propagation paths (Fig. 10b). It is called ‘active perturbation’ and results in

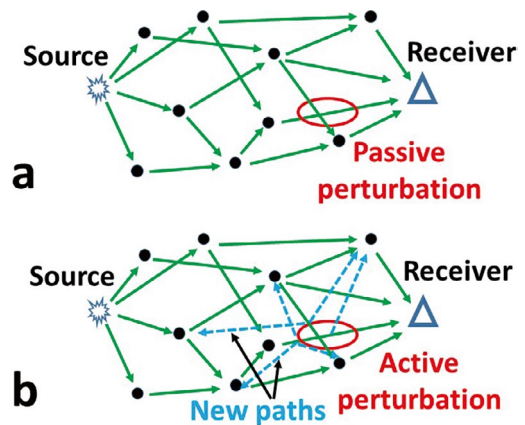


Fig. 10 Sketch showing the difference between active and passive perturbations. **a** A velocity variation inside the medium is a passive perturbation which modifies the travel time of the seismic waves but not their paths. **b** A modification of the structure due to an intrusion or a fault opening is an active perturbation which modifies the wave paths

changes in the waveforms. In both cases, the key point is to define the relationships between localized medium perturbations and modifications of the observables. These relationships are contained in sensitivity kernels which depend on the relative position of the station pair and the perturbation.

The travel time of a wave field in the diffusion regime is given by

$$t = \int_V \kappa_{tt}(s_1, s_2, x_0, t) dV(x_0) \quad (19)$$

where $\kappa_{tt}(s_1, s_2, x_0, t)$ is the distribution of travel time of multiply scattered waves from a source at location s_1 to a receiver at location s_2 after visiting a location x_0 (Pacheco and Snieder 2005). This distribution is a statistical representation of the time spent in each part of the medium.

Small perturbations δs in the slowness s of the medium ($\delta s/s < 1$) modify the mean travel time as (Pacheco and Snieder 2005; Planès et al. 2014):

$$\delta_t(t) = \int_V \kappa_{tt}(s_1, s_2, x_0, t) \frac{\delta s}{s}(x_0) dV(x_0) \quad (20)$$

where $\frac{\delta s}{s}(x_0)$ represents the relative slowness variation produced in the medium at location x_0 .

The variations of travel time can be measured by CWI and are related to the AVV:

$$\left. \frac{\delta v}{v} \right|_{app}(t) = -\frac{\delta_t(t)}{t} = -\frac{1}{t} \int_V \kappa_{tt}(s_1, s_2, x_0, t) \frac{\delta s}{s}(x_0) dV(x_0) \quad (21)$$

The AVV can thus be considered as weighted averages of the slowness perturbations, the weights being the sensitivity kernels κ_{tt} . They are functions of the travel time t of the diffuse wave field which is taken as the delay in the coda used for the calculations.

The changes in waveform produced by a structural perturbation of the medium can be quantified by the decorrelation coefficient:

$$DC(t) = 1 - \frac{\int_{t_1}^{t_2} u_1[t'] \cdot u_2[t'] dt'}{\sqrt{\int_{t_1}^{t_2} u_1^2[t'] dt' \cdot \int_{t_1}^{t_2} u_2^2[t'] dt'}}, \quad (22)$$

where u_1 and u_2 are the waveforms before and after the changes, respectively, and t is the centre of the coda window bounded by delays t_1 and t_2 on which the calculation is done. The decorrelation is proportional to the cross-section σ of the new defect and to the wave velocity c :

$$DC(t) = \frac{c\sigma}{2} \int_V \kappa_{DC}(s_1, s_2, x_0, t) dV(x_0), \quad (23)$$

where s_1 , s_2 , and x_0 are the locations of the two stations and of the new scatter (Rossetto et al. 2011; Planès et al. 2014; Margerin et al. 2016).

The evaluation of the sensitivity kernels is not an easy task and several authors have addressed the problem of calculating these kernels by analytical or numerical approaches (see review in Zhang et al. 2021). Pacheco and Snieder (2005) proposed an analytical expression for the case of isotropic scattering of acoustic waves in the diffusion approximation:

$$\kappa_{tt}(s_1, s_2, x_0, t) = \frac{\int_0^t I(s_1, x_0, t-t') I(x_0, s_2, t') dt'}{I(s_1, s_2, t)}. \quad (24)$$

$I(s_1, s_2, t)$ represents the wave intensity at receiver location s_2 due to a unit impulse at source s_1 . In a 2D infinite non-absorbing medium, the intensity can be taken as the solution of the diffusion equation:

$$I(r, t) = \frac{1}{2\pi Dt} \exp\left(\frac{-r^2}{4Dt}\right) \quad (25)$$

where r is the distance between the source and the receiver and D is the coefficient of diffusion. Figure 11a displays examples of sensitivity kernel.

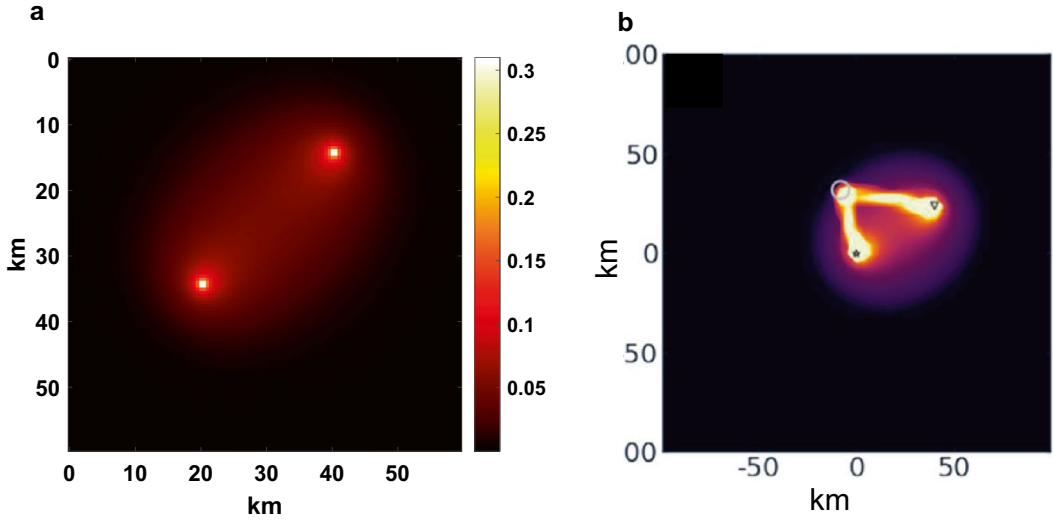


Fig. 11 Sensitivity kernels. **a** In a homogeneous scattering medium. **b** In a medium with a region of stronger scattering representing a volcano adapted from van Dinther et al. (2021)

When the source and the receiver are at the same location (for example when using cross-correlation between components of a single station), the sensitivity kernels in the 2D and the 3D geometries are respectively (Pacheco and Snieder 2005)

$$\kappa_{2D}(r_0, t) = \frac{1}{2\pi D} \exp\left(\frac{-r_0^2}{2Dt}\right) \cdot K_0\left(\frac{-r_0^2}{2Dt}\right) \quad (26)$$

$$\kappa_{3D}(r_0, t) = \frac{1}{2\pi D r_0} \exp\left(\frac{-r_0^2}{Dt}\right) \quad (27)$$

where r_0 is the distance between the station and the perturbation and K_0 is the modified Bessel function of the second kind. The solutions derived from the diffusion equation are approximations valid for $t \gg \frac{l^2}{c}$.

For short times and when the perturbations are close to the source or the receiver, a solution of the radiative transfer equation provides a more general and precise representation of the intensity I (Shang and Gao 1988; Sato 1993; Paasschens 1997; Planès et al. 2014). In this case, for 2D geometry and isotropic scattering, the intensity is

$$I_{2D}^{RT}(r, t) = \frac{1}{2\pi r} \exp\left(-\frac{ct}{l}\right) \delta(ct - r) + \frac{1}{2\pi lct} \left(1 - \frac{r^2}{c^2 t^2}\right)^{-\frac{1}{2}} \cdot \exp\left[\frac{\sqrt{c^2 t^2 - r^2} - ct}{l}\right] \cdot \Theta(ct - r) \quad (28)$$

where l is the mean free path, c is the wave velocity, δ is the Dirac function, and Θ is the Heaviside function.

Margerin et al. (2016) demonstrated that different sensitivity kernels should be used to characterize the passive and active perturbations of the medium associated with apparent velocity variations and decorrelations, respectively. Their calculations also take into account the scattering anisotropy using a radiative transfer theory and they obtained a more general expression for the sensitivity kernel K_u which can be substituted into Eq. 24. Margerin et al. (2019), Xu et al. (2022) and Barajas et al. (2022) extended the previous work by including the coupling between body and surface waves and by studying the temporal evolution of the sensitivity kernels of body and surface waves. Snieder et al. (2019) and Zhang et al. (2021) considered the elastic case and perturbations of the P- and S-wave velocities. van Dinther et al. (2021)

computed sensitivity kernels for non-uniform distribution of scattering strength in the cases of structures including either a volcano, two contiguous half-spaces or a fault zone. The resulting kernels are very different to those calculated for homogeneous media (Fig. 11b). In all these complex cases, there is no analytical formulation of the sensitivity kernels. They are obtained by numerical simulations which require intensive calculations.

In order to address the issue of the depth sensitivity of the coda wave to a perturbation, Obermann et al. (2013a, 2016) introduced a time varying combination of body and surface waves sensitivity kernels. In the case of a homogeneous scattering half-space, they showed that the sensitivity of surface waves is dominant at early times in the coda while body waves sensitivity becomes more important at time larger than about 8 mean free times $t^* = l^*/c$ ($t^* = l^*/c$) (Fig. 12). Using the same combination of body and surface waves sensitivity kernels and working in a unique frequency band, Obermann et al. (2018) could estimate the depth location of medium perturbations.

Volcanoes are very heterogeneous structures with rough topography in which seismic waves

are strongly scattered. In this type of medium, the scattering can be considered as isotropic (Yamamoto and Sato 2010) and thus the approximation $l = l^*$ is valid. Furthermore, the seismic velocities present rapid increases in the first layers of volcanoes. For example, S-wave velocity varies in average from about 300 ms^{-1} at the surface to more than 1500 ms^{-1} at 500 m depth (Lesage et al. 2018b). Several observations suggest that the mean free path also increases with depth (Wegler 2003; Parsieglia and Wegler 2008; Kanu and Snieder 2015). The low velocity layers close to the surface act as waveguides and enhance the surface waves with respect to the body waves. The consequence is that the sensitivity kernels of surface waves are dominant in the early coda until lapse-time much longer than the value of $8 t^*$ estimated by Obermann et al. (2013a; 2016) in the case of a homogeneous half-space. This justifies the assumption of considering seismic codas as dominated by surface waves (Obermann et al. 2014a; Lesage et al. 2014). Several methods of perturbation location either in 2D or in depth require this assumption.

3.4.3 Location in the Horizontal Plane

The spatial distribution of the slowness perturbations in the horizontal plane can be estimated by solving Eq. 21 as a linear least squares inverse problem (Larose et al. 2010; Froment 2011; Planés 2013; Obermann et al. 2013b; Lesage et al. 2014; Machacca et al. 2019). A set of AVVs calculated for different pairs of stations and in several sections of the coda are used as data. This equation can be rewritten as

$$d = G \cdot m \quad (29)$$

where the data vector d contains the AVVs, G is the matrix of sensitivity kernels $\kappa(s_1, s_2, x_0, t)$, and the components of the model vector m are the velocity perturbations at each position $\frac{\delta v}{v}(x_0)$. The solution is given by

$$m = C_m G^t (G C_m G^t + C_d)^{-1} d \quad (30)$$

where G^t is the transpose matrix of G and C_d is the covariance matrix of the data. The physical correlation between the discrete elements of

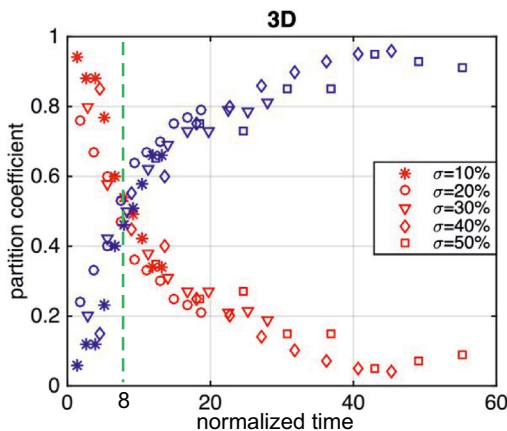


Fig. 12 Partition coefficients between the sensitivity kernels of body and surface waves as a function of the time lag normalized by the mean free time t^* . The sensitivity of surface waves (red symbols) is higher for normalized time lag less than 8 (vertical green line) than that of body waves (blue). Adapted from Obermann et al. (2016)

the model is taken into account by a covariance matrix such as

$$C_m(x_i, x_j) = \left(\sigma_m \frac{\lambda_0}{\lambda} \right)^2 \exp \left(- \frac{(x_i - x_j)^2}{\lambda^2} \right) \quad (31)$$

where σ_m is the a priori error on the model, λ_0 is the grid interval, λ is a correlation length which controls the smoothness of the model, and x_i and x_j are the position vectors of two cells of the model. The restitution index (Vergely et al. 2010) is calculated by summing the elements of the rows of the resolution matrix (Backus and Gilbert 1970) $R = C_m G^t (G C_m G^t + C_d)^{-1} G$. A value of the index close to one indicates that the corresponding element of the model is well recovered while a low value is associated with a poor estimation. A similar approach can be used with the decorrelation to locate structure perturbations (Larose et al. 2010).

Obermann et al. (2013b) presented the first application of this method on volcanoes. They calculated velocity variations in a period of six months in 2010 during which two eruptions occurred at Piton de la Fournaise. They located a region with significant velocity decrease associated to the first and largest eruption. They also located the perturbations that produced decorrelation for the two eruptions. All the obtained locations are close to the corresponding eruption sites (Fig. 13). Using similar approaches, Lesage et al. (2014), Budi-Santoso et al. (2016), Sánchez-Pastor et al. (2018), and Machacca et al. (2019) detected and located velocity or structural perturbations in Volcán de Colima, Merapi, El Hierro, and Ubinas volcanoes, respectively.

As discussed in Sect. 2.3, the mean free path in the medium is generally poorly known and its value spans more than one order of magnitude, according to the volcanoes and/or to the methodology used in its estimation (Table 1). A large mean free path value causes the sensitivity kernel to be more widely spread and thus the corresponding size of the estimated perturbation broader. However, the location of the perturbation is largely independent of the mean free path (Obermann et al. 2013b).

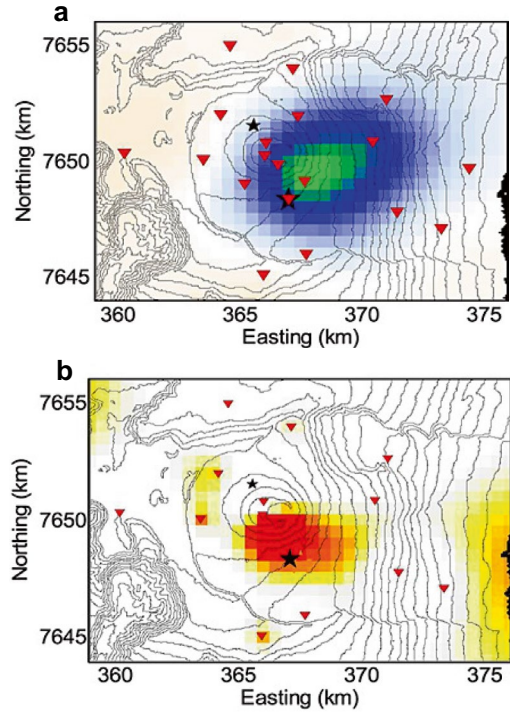


Fig. 13 Location in the horizontal plane of. **a** A velocity perturbation and. **b** A structural perturbation associated with an eruption of Piton de la Fournaise volcano, La Réunion Island. The red triangles are the seismic stations and the stars indicate the eruptive vents. Adapted from Obermann et al. (2013b)

When interpreting the results of a location, one must keep in mind that they are based on simplifying approximations, especially for the calculation of the sensitivity kernels given by Eq. 24. The use of more realistic kernels, by taking into account the scattering anisotropy (Margerin et al. 2016), the coupling of body and surface waves (Margerin et al. 2019; Xu et al. 2022; Barajas et al. 2022), the elastic case (Snieder et al. 2019; Zhang et al. 2021), and non-uniform distribution of scattering strength (Fig. 11b, van Dinther et al. 2021), would provide more reliable and precise locations in spite of higher computational costs.

3.4.4 Location in Depth

The depth of the perturbations can also be estimated by using the dependency of the AVV to the frequency. Indeed, because coda waves are

assumed to contain mainly surface waves, the AVV is more sensitive to deep sources of perturbation at low frequency than at high frequency. By assuming that Rayleigh waves are dominant in the coda, the depth distribution of the perturbation can be estimated by inverting the relation

$$\left. \frac{\delta v}{v} \right|_{app}(f) = - \int \kappa_z(z, f) \frac{\delta s}{s}(z) dz \quad (32)$$

where $\left. \frac{\delta v}{v} \right|_{app}(f)$ is the AVV calculated at a given station pair and for different frequency ranges. The sensitivity kernel $\kappa_z(z, f)$ is the derivative of

the Rayleigh phase velocity c with respect to the S-wave velocity v_s (Lesage et al. 2014)

$$\kappa_z(z, f) = \frac{dc}{dv_s}(z, f). \quad (33)$$

Lesage et al. (2014) calculated the velocity decrease produced by a strong tectonic earthquake on Volcán de Colima in several frequency ranges between 0.3 and 1 Hz. They showed that the variations occurred at depth less than 800 m below the surface while the restitution index indicated reliable results up to 2 km depth (Fig. 14).

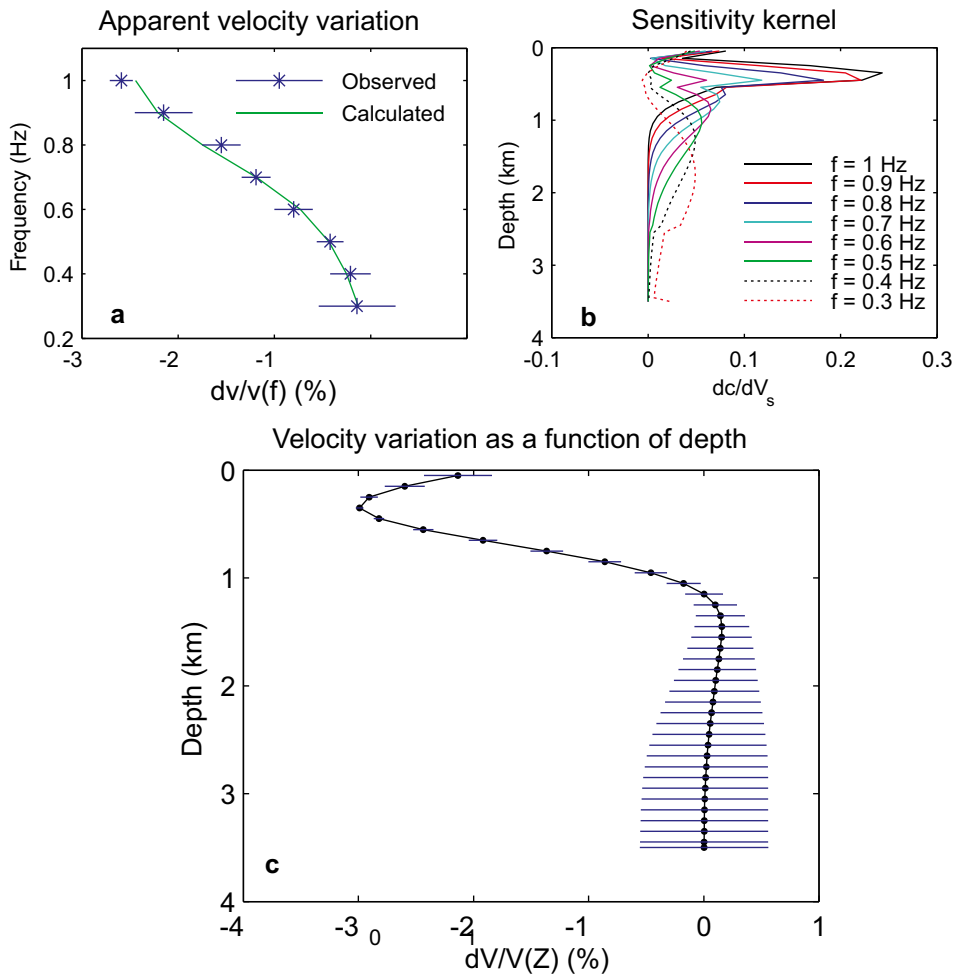


Fig. 14 Location in depth of a velocity perturbation due to strong ground shaking in Volcán de Colima, Mexico. **a** Observed velocity variation and uncertainty (blue) and calculated velocity variation (green) as a function

of frequency; **b** Sensitivity kernels of Rayleigh waves as a function of depth for several frequencies; **c** Estimated velocity variation as a function of depth, with uncertainties. Adapted from Lesage et al. (2014)

4 Physical Processes

Velocity variations are observed on many volcanoes before, during and after eruptions, as well as during quiescence. In order to use these observations for volcano monitoring, it is important to interpret them in terms of physical processes. This section presents an overview of the large variety of mechanisms that can generate decreases or increases of seismic wave velocities in volcanic structures. The identification of the process(es) that produces a given observed velocity variation is a complex issue that still deserves much research.

4.1 Effects of Stress on Rock Mechanical Properties

Volcanic edifices are made of rocks submitted to time varying stress fields. The behaviour of these rocks can be studied with laboratory experiments using axial or triaxial presses that reproduce the stress conditions at depth. In a typical experiment, a small cylindrical rock sample is placed in a press which can apply a confining pressure and an axial

stress. The P- and S-wave seismic velocities are measured in several directions parallel or perpendicular to the cylinder axis by using piezoelectric transducers. Figure 15 displays the stress–strain curve obtained during experiments where the strain is progressively increased up to the sample rupture. At small strains, the stress increases almost linearly with the deformation indicating an elastic regime. During this stage, the sample volume decreases due to the closure of microcracks, thereby increasing seismic velocity. For increasing strain, when the corresponding stress is larger than approximately 50% of the rupture strength, new cracks appear with their plane parallel to the axial stress leading to decrease of seismic velocity. These crack openings are accompanied by acoustic emission produced by seismic ruptures and by volume increase. This stage corresponds to an irreversible plastic deformation associated with rock damaging. When the strain is still increased, new cracks appear, coalesce each other and localize along shear bands which develop until the sample rupture. Several parameters, such as the temperature, the confining pressure, the fluid saturation, or the initial density of cracks can modify the rock

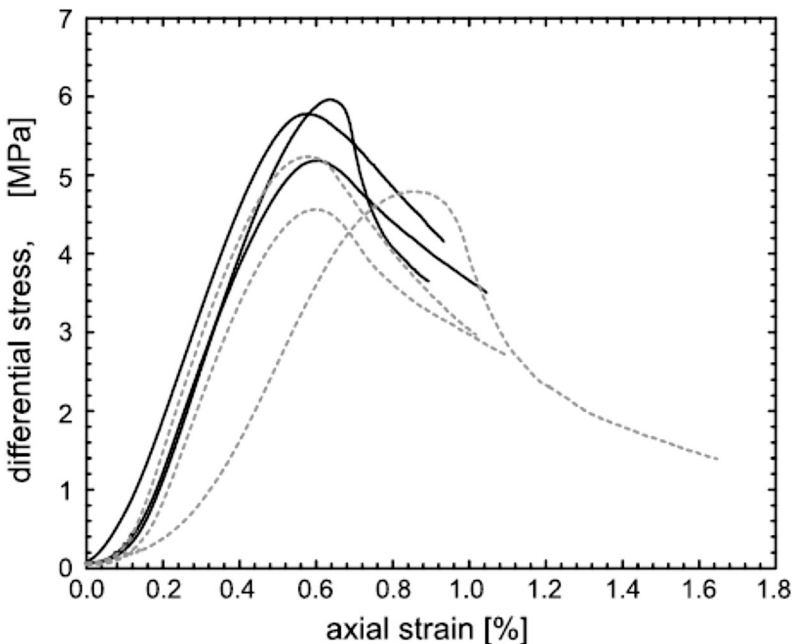


Fig. 15 Uniaxial stress–strain curves for several samples of rock from Whakaari volcano, New Zealand. The samples are either dry (solid lines) or saturated (dashed grey lines). Adapted from Heap et al. (2015)

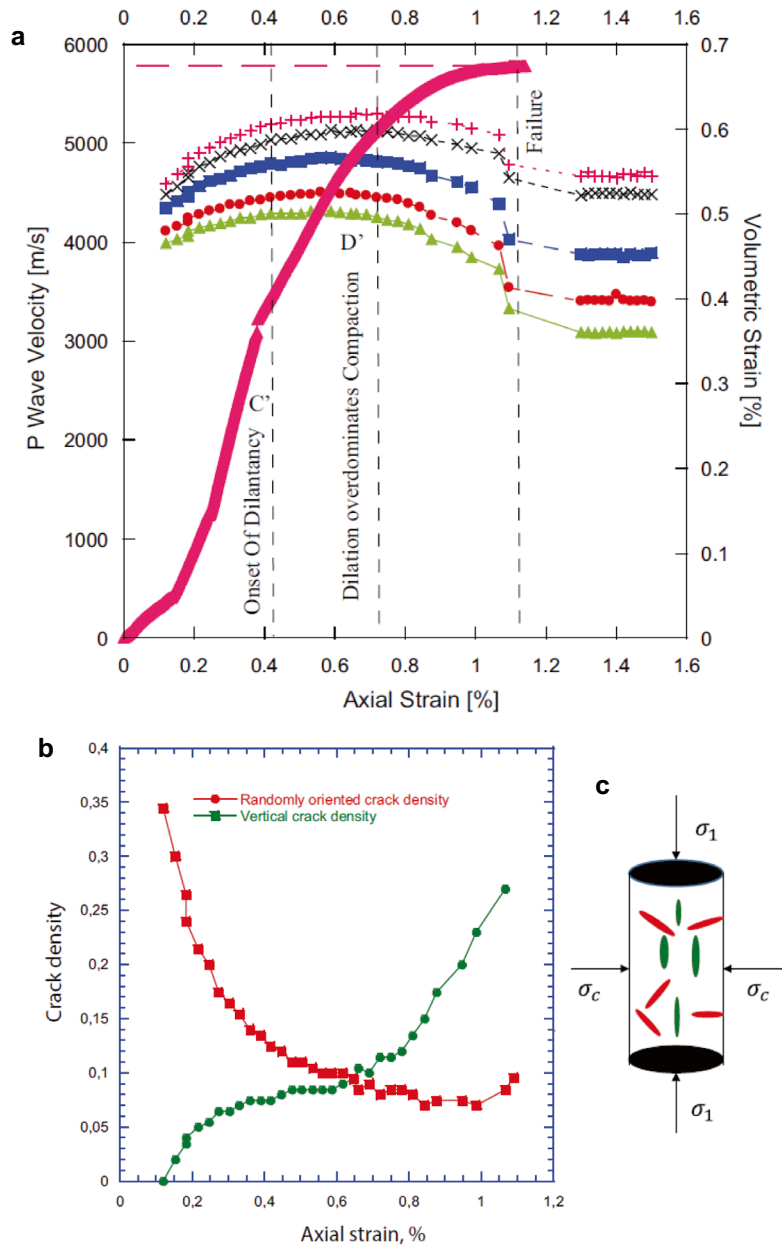


Fig. 16 **a** Velocity of compressive wave and volumetric strain as a function of axial strain during a triaxial experiment on heat treated andesite sample. The velocity is measured in several directions with respect to the main stress under a confining pressure of 30 MPa. **b**

Axial crack density (green) and randomly oriented crack density (red) as a function of axial strain. **c** Sketch showing axial (green) and randomly oriented (red) cracks. Adapted from Li et al. (2019)

behaviour under strain (Fortin et al. 2011; Li et al. 2019). The closure and opening of microcracks and pores due to stress variations modifies the seismic velocities of the rock.

Figure 16 presents the variations of V_p in directions radial and axial with respect to the main stress axis, as a function of the strain. For small strain, one observes a progressive increase

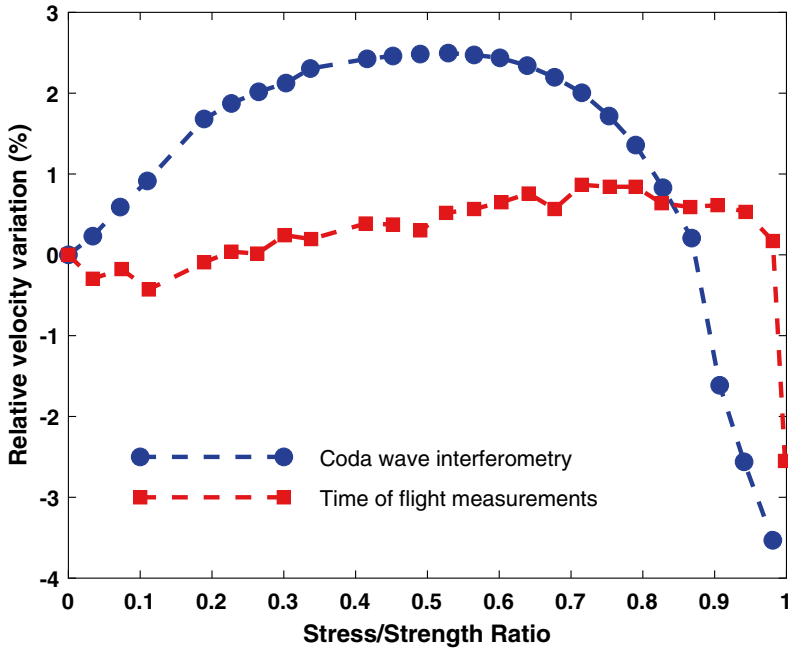


Fig. 17 Relative velocity variation of a concrete sample as a function of stress/strength ratio up to the sample rupture. The velocity is measured in the direction of the

main stress axis using either the time of flight (red) or coda wave interferometry (blue). Adapted from Shokouhi et al. (2010)

of all the velocities due to the closure of cracks perpendicular to the stress axis. For larger strain, the velocities decrease up to the rupture. This behaviour is accompanied by changes in seismic anisotropy (Nur 1971; Fortin et al. 2011). In some experiments (Shokouhi et al. 2010; Shokouhi and Niederleithinger 2012), the velocity variations are measured by CWI which yields to a greater sensitivity to stress changes than the measurements of ballistic waves velocities (Fig. 17).

4.2 Sources of Stress Variations

The variations of seismic velocities within a volcano depends on several complex phenomena and rock properties: (1) the pre-existing stress field and, in particular, the value of the deviatoric stress that can bring the rocks closer to or farther from the rupture; (2) the incremental stress field whose components can be either positive or negative; (3) the distribution of cracks

and fractures in the structure and their orientations with respect to the main stress components (Hotovec-Hellis et al. 2022; Muzellec et al. 2023).

While it is difficult to know the initial state of stress of a volcano, the variations of the stress are generally caused by different internal or external phenomena. The most common one, especially during pre-eruptive periods, is associated with magma intrusion which modifies the pressure within the magmatic system, reservoir, dike or sill. The effect of pressurization or depressurization of the plumbing system on the stress field in the surrounding medium can be evaluated using analytical and numerical models.

Let us consider as a first example a pressurized spherical reservoir in an elastic half-space. Analytical solutions for the displacement field in the case of a point source have been proposed by Anderson (1936) and Yamakawa (1955) and were popularized by Mogi (1958). McTigue (1987) calculated more general solutions for

the displacement and stress fields in the case of an overpressure in a finite-size sphere. Several components of the stress tensor are displayed in Fig. 18. In almost all the medium surrounding the reservoir, the mean normal stress (the tensor trace divided by three) is positive which corresponds to tensile stress. However, the radial component, with respect to the sphere centre, is compressive (negative), while the two orthoradial components are tensile (positive). This complex pattern results from the finite size of the sphere and the free surface effect. If the distribution of cracks in the surrounding rocks

is isotropic, a pressure increase in the reservoir would produce tensile mean normal stress and thus velocity decrease.

However, in several cases such as the pre-eruptive period of the 2018 Kilauea eruption and during its caldera collapse, velocity increases were observed during the pressurization of the shallow reservoir and the inflation of the edifice. The presence of many ring faults around the caldera, which are more sensitive to radial compressive stress, could explain these observations (Hotovec-Ellis et al. 2022; Muzellec et al. 2023). An irregular topography can also

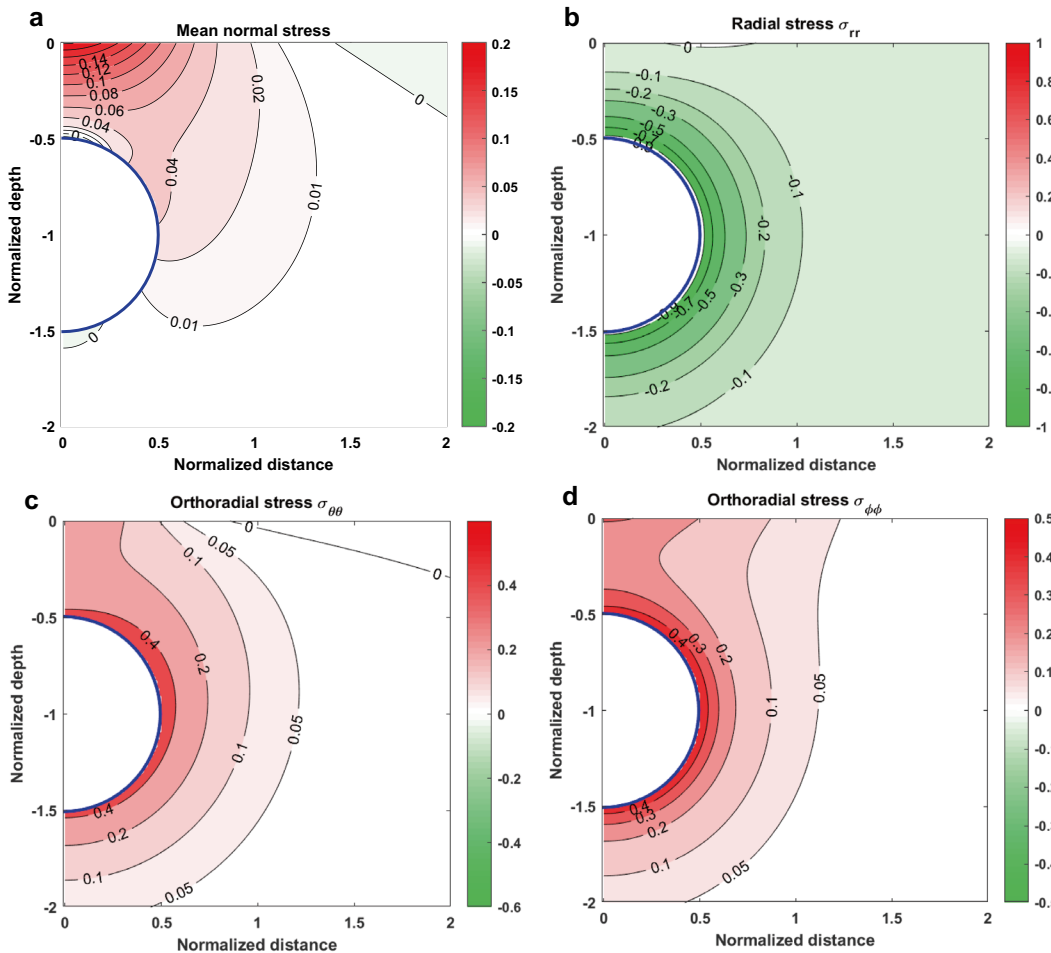


Fig. 18 Distribution of stress in the surrounding of a pressurized sphere embedded in an elastic half-space (McTigue 1987). The pressure and the stress values are normalized by the overpressure and the distances are

normalized by the depth of the sphere center. The radius/depth ratio is 0.5 and the Poisson coefficient is 0.25. **a** Mean normal stress (tensor trace divided by 3). **b** Radial stress component; **c** and **d** Orthoradial stress components

introduce more complex displacement and stress fields (McTigue and Segall 1988; Cayol and Cornet 1998).

As an alternative and complementary approach, Got et al. (2019) proposed a model of shallow pressurized reservoir in a damaging medium, using the finite element progressive damage scheme of Amitrano and Helmstetter (2006, and references herein). At the beginning of the process, an isotropic damaged zone appears around the cavity. After that, due to the free-surface effect, anisotropic shear bands develop and localize along reverse faults that propagate to the surface (Fig. 19). As described below (Sect. 4.4), rock damaging produces velocity decreases.

As illustrated by the preceding examples, both elastic and elasto-plastic processes can generate velocity variations. However, the sign and amplitude of the velocity changes in the medium depend on many factors such as: the initial stress state, the type, position and depth of the pressure source, the distribution and orientation of cracks and fractures in the rock. The resulting observed AVVs also depend on the relative position of the seismic stations and the sources of perturbation (Budi-Santoso et al. 2016), the frequency ranges and time delay interval in the coda, as well as the seismometer components used for

the calculations. Therefore, some caution needs to be exercised when interpreting these complex phenomena.

Several processes can produce variations of the vertical stress by gravitational loading/unloading of the structure inducing velocity changes. Rainfall was identified as a major cause of velocity variation through loading and modification of pore pressure (see Sect. 4.3) (Sens-Schönfelder and Wegler 2006; Donaldson et al. 2019). Similarly, velocity changes have been observed due to the presence of snow. Seasonal increases in velocity in regions with snow cover have been interpreted as pore space reduction and crack-closing in response to increased surface loading (Hotovec-Ellis et al. 2014; Wang et al. 2017; Donaldson et al. 2019). While this is the most common observation, snow loading has also been found to cause velocity decreases (Taira and Brenguier 2016). In this case, increases in the surface load are interpreted to drive hydrothermal fluid diffusion, leading to crack opening and subsequent velocity decrease. The sign of velocity change observed may therefore be dependent on whether a large fluid body exists in the studied area (Silver et al. 2007; Taira and Brenguier 2016). In any case, rainfall and snowfall are thought to be the main origin of the seasonal variations observed at many sites (Sens-Schönfelder and Wegler 2006; Hotovec-Ellis et al. 2014; Donaldson et al. 2019). Similarly, caldera collapses are generally associated with velocity decrease or increase due to the unloading effect and/or the corresponding pressure variations in the magmatic system (Anggono et al. 2012; Duputel et al. 2019; Hotovec-Ellis et al. 2022). They can also produce the decorrelation of the NCF due to the change of topography.

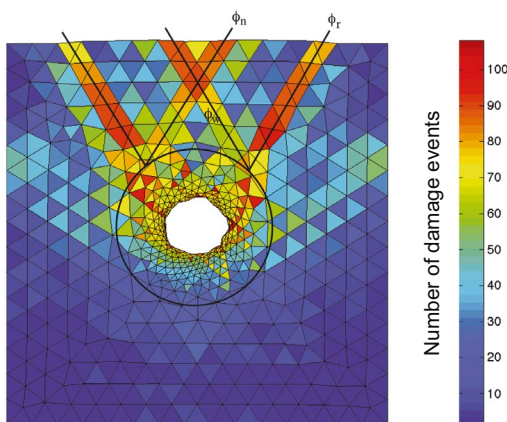


Fig. 19 Damage distribution due to a pressurized reservoir. The number of damage events in each element of the numerical model is indicated by the color scale. Reverse (ϕ_r) and normal (ϕ_n) faults result from a free surface effect. Adapted from Got et al. (2019)

4.3 Hydrothermal Fluids

Volcanoes often contain hydrothermal systems intersected between the surface and magma reservoirs. They are typically composed of fluids (gas, water/brine) which are circulating in

fractured and altered rocks. Such altered material is often porous and permeable encompassing a wide spectrum of physical properties which, as shown in laboratory studies, depend on temperature (e.g., Heap et al. 2017). Rock alteration above 200 °C can, for example, result in weakening or rock strengthening through pore- and crack-filling precipitation (Heap et al. 2017 and references therein).

The wide range of physico-chemical and mechanical behaviours of volcano-hydrothermal systems considerably affect seismic wave propagation. Seismic velocity changes in hydrothermal reservoirs are primarily due to poroelastic effects (Doetsch et al. 2018). The increase in hydrothermal fluids content generally decreases seismic wave velocity by modifying the effective stress, i.e., the net stress applied to the rock due to both mechanical pressure and pore pressure; an increase in pore pressure resulting in a decrease of the elastic moduli and wave velocity (Doetsch et al. 2018). The velocity of rocks varies with their saturation in gas (Lumley 2010) and water (Fortin et al. 2011; Lesage et al. 2018b), as well as the type of fluid they contain (Clarke et al. 2020), the nature of host rocks (Heap et al. 2017), or their alteration (Pola et al. 2012). For example, tuffs are more sensitive to saturating fluid compared to lavas (Clarke et al. 2020). P wave velocities can vary between 2.2 km s⁻¹ to 1.2 km s⁻¹ for consolidated and unconsolidated tephra, respectively (Jolly et al. 2012). Overall, the porosity controls the P wave velocity through the volume and the shape of the pores (Winkler and Murphy 1995). In general, rocks with higher porosity and fracture density have lower P-wave velocities (Heap et al. 2017). Conversely, mineral precipitation can block pores and cracks thereby decreasing rock permeability (Kennedy et al. 2020) and increasing their seismic velocity (Caudron et al. 2021).

Seismic interferometry has been applied to detect processes occurring in the realm of volcano-hydrothermal systems. Stress perturbations and a hydrothermal fluid surge have been found beneath Hakone hydrothermal areas using seismic interferometry and more specifically a horizontal polarization anomaly, following

the Tohoku Oki earthquake (Saade et al. 2019). Caudron et al. (2022) also observed abnormal AVV close to the summit of Mt Ontake possibly reflecting a period of reversible but disturbed stress field induced by pressurized fluids on the eastern flank of the volcano a few months before it erupted. Earlier, Mordret et al. (2010) and Caudron et al. (2015) had suggested seismic velocity reductions associated with gas influx in hydrothermal systems. On the other hand, increases of seismic velocity have been observed due to progressive sealing of the shallow portions of hydrothermal system (Yates et al. 2019; Caudron et al. 2021, 2022).

Seismic velocity can also be used as a proxy to identify pressurized fluids within volcanoes. Areas where the sensitivity of velocity to stress variations is higher have been correlated with the presence of hydrothermal fluids that reduce the effective confining pressure. This leads to greater crack density and increases the sensitivity of the medium to pressure fluctuations (Brennguier et al. 2014). Consequently, geothermal reservoirs might be particularly sensitive to external stress changes (Taira et al. 2018). Taira et al. (2018) have suggested that ground shaking in Salton Sea geothermal reservoirs can increase apparent crack density through unclogging of fractures due to pore pressure fluctuations, thereby reducing seismic velocity. Brennguier et al. (2014) used stress sensitivity to map pressurized fluids below volcanoes following the 2011 Tohoku-Oki earthquake in Japan. At the volcano scale velocity changes can be restricted to some areas (Budi-Santoso et al. 2016). Prior to the 2014 eruption at Mt Ontake, significant AVV was only measured above volcano-hydrothermal systems, where stress sensitivity is enhanced (Caudron et al. 2022).

4.4 Damaging, Healing, Softening, Sealing

The mechanical properties of rocks can be modified by several processes which generate velocity variations. For example, when an earthquake occurs, this weakens the surrounding medium and decreases its elastic moduli. The concept

of linear damage was introduced by Kachanov (1958) who defined the damage coefficient as the proportion of damaged area $D = \delta A/A$, where A is the section of the sample and δA is the damaged area. He also introduced the effective Young and shear moduli of the damaged material as $E' = (1-D)E$ and $G' = (1-D)G$, where E and G are the moduli of the intact rock (Carrier et al. 2015). From these definitions, it follows:

$$D = \frac{\delta A}{A} = -\frac{G' - G}{G} = -\frac{\delta G}{G} \quad (34)$$

A perturbation of the shear modulus is associated with a variation of the S-waves velocity $V_s = \sqrt{\frac{G}{\rho}}$, where ρ is the density. At constant density, one can write:

$$\frac{\delta V_s}{V_s} = \frac{1}{2} \frac{\delta G}{G} = -\frac{1}{2} \frac{\delta A}{A} \quad (35)$$

These relations show that the local relative variation of S-wave velocity produced by a rupture is proportional to the damaged area δA . When seismic waves propagate through the weakened zone, they are slowed and delayed, which can

be detected by CWI. During a sequence of VT activity, each event produces a local perturbation. The set of perturbations has a cumulative effect on the observed AVV. Olivier et al. (2019) calculated the cumulative rupture area of the seismic events during the pre-eruptive period of the 2018 Kilauea eruption, in order to model the observed velocity decreases. Muzellec et al. (2023) improved this approach by weighting each local perturbation by sensitivity kernels used to locate the velocity variations in the horizontal plane and in depth (Eqs. 24 and 33). The curves they calculated for the Kilauea eruption fit well the observed AVVs using different station pairs (Fig. 20). Note that this approach can only reproduce velocity decreases.

Large tectonic earthquakes that occur close to volcanoes frequently induce sharp velocity drops (e.g. Battaglia et al. 2012; Lesage et al. 2014; Machacca et al. 2019). For example, 15 earthquakes with magnitude > 6 generated velocity decreases on Volcán de Colima, Mexico, from 1998 to 2013 (Lesage et al. 2014). The closest event ($M=7.4$) produced a velocity

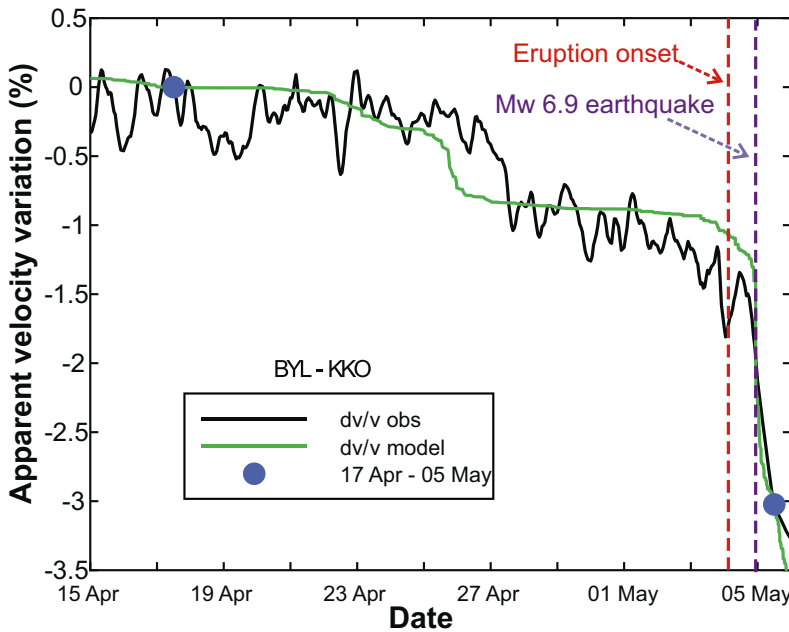


Fig. 20 Comparison of observed velocity variations before the 2018 Kilauea eruption (black curve) and the calculated velocity variations (green curve) using a

damaging model based on the seismic activity of the volcano. Adapted from Muzellec et al. (2023)

drop of up to 2.6% close to the volcano summit, while no velocity change was detected in the epicentre region. The velocity decrease was localized in the shallow layers (<800 m) of the edifice. The velocity recovered its previous value in approximately 5 years. This behaviour is best explained by the softening caused by seismic shaking of the granular material (Guyer and Johnson 1999; Johnson and Jia 2005), a phenomenon also observed in poorly consolidated sedimentary rocks (Rubinstein and Beroza 2004). The inverse process, which produces the recovery of the velocity to its initial value, is due to the progressive healing of the rock grains to each other. It follows a time logarithmic law characteristic of slow dynamics behaviour (Johnson and Sutin 2005).

Much attention has been given to the search of precursors to gas-driven eruptions. Several studies have recently shown relative velocity increases along time (Yates et al. 2019; Caudron et al. 2021, 2022). These have been ascribed to the progressive sealing of the vents through precipitation of minerals (e.g., sulfates, sulfur or silica (Christenson et al. 2010)) in pores or cracks. The timescales for such processes remain unclear but could be as short as a few hours (Kennedy et al. 2020) and as long as several years (Christenson et al. 2010; Caudron et al. 2021).

4.5 Sources of Decorrelation

Along with changes in noise sources, several processes can produce decorrelations. These can be observed following structural changes in the scattering media. For example, the dramatic earthquake activity around the Mt. Þorbjörn was accompanied by waveform decorrelations that suggested permanent crustal damage (Cubuk-Sabuncu et al. 2021). Yet, they have also been observed prior to eruptions (e.g., Bennington et al. 2015; Yates et al. 2019; Hirose et al. 2022) and interpreted as structural perturbations in the scattering properties possibly induced by fluid accumulation. Obermann et al. (2013b) located structural

changes close to the site of a forthcoming eruption at Piton de la Fournaise volcano. They interpreted the observed decorrelations as due to magma feeding channel prior the eruption. At Ubina volcano, medium perturbations producing decorrelations were located on a weak area associated with an ancient flank collapse (Machacca et al. 2019). In volcano-hydrothermal settings, fluid injection could also induce waveform decorrelation as shown in laboratory setups (Thery et al. 2020; Caudron et al. 2021). Change of volcano topography induced by lava flows or collapse can also induce waveform changes (e.g., Hotovec-Ellis et al. 2022).

5 Conclusions and Perspectives

The extraction of Green functions by ambient seismic noise cross-correlation and the detection of perturbations of wave propagation by coda wave interferometry are major advances in seismology. At the time of writing this chapter, seismic interferometry-based studies have been carried out for about 15 years. A large part of these studies are applied to volcanoes due to their dynamic nature and their scattering structure. It is thus important to assess the performances and limitations of these relatively new techniques for volcano monitoring. Some perspectives of improvement and research can also be drawn for the coming years.

5.1 Development of Theoretical Studies

The propagation of coda waves in heterogeneous and scattering structures such as volcanoes is a complex and still poorly understood phenomenon. Further research on this topic would be useful to improve the interpretation of the observations. For example, a better knowledge of the coda content and the partition of surface and body waves along the coda in the case of volcanic structure is necessary to improve the location of the perturbations (Obermann et al.

2016). These locations would require more realistic sensitivity kernels (Zhang et al. 2021; Xu et al. 2022; Barajas et al. 2022). Studies on the propagation of coda waves in the case of cross-components of single station NCFs would also be useful. Finally, the influence of an anisotropic distribution of crack orientation in rocks (Nur 1971; Mavko et al. 1995; Schubnel and Guéguen 2003) and the interpretation of velocity variations that depend on the pair of components used (Machacca et al. 2019) should be topics of further research.

5.2 Seismic Sensors and Networks

A strong advantage of CWI is that it can detect velocity variations with only one sensor, if it is located close enough to the active region. This feature is useful to monitor dormant or remote volcanoes. Moreover, using one component per station of a seismic network, the number of NCFs that can be calculated is $N(N-1)/2$, where N is the number of stations. The amount of NCFs can be strongly increased when combining all the components of the pairs of the seismometers (ZZ, NN, EE, ZN, ZE, NE). Research on the application of cross-components NCFs is still required to evaluate their usefulness in volcano monitoring. It can produce new observables, such as the horizontal polarization anomaly of surface waves that can help detecting hydrothermal fluid surge (Saade et al. 2019).

The geometry of the network has probably little influence on its ability to detect velocity changes, although this point has not been studied in detail up to now. This is because coda waves propagate inside large ellipsoidal regions around the stations, producing an averaging effect and higher sensitivity to medium changes than with ballistic waves. However, it is ideal to have both close and remote stations from the crater and to use some pairs of stations whose paths cross the active zone. Moreover, a network with more than 6–10 spatially distributed stations is required to locate the perturbations in the horizontal plane. Further improvements

could be obtained by using several dense arrays of sensors, such as seismic nodes, that would allow to extract body waves which usually sample deeper regions than surface waves (Nakata et al. 2016; Brenguier et al. 2016). The use of Distributed Acoustic Sensing with optical fibre, that can be considered as very dense array, is also very promising and will offer new opportunities of observing AVV (Jousset et al., chapter Fiber optic monitoring, this book).

5.3 Data Processing

Most studies applied to volcanoes use standard procedures of data processing, such as spectral whitening, windsorizing, stacking of correlation functions, MWCS or stretching. These methods are efficient and generally produce good results. They can easily be integrated in monitoring systems and carried out in real-time, as already done in some volcano observatories (Duputel et al. 2009; Lecocq et al. 2014). However, in some cases, it is interesting to use alternative approaches and pre-processing techniques (covariance matrix eigenspectrum (Seydoux et al. 2017)), advanced algorithms for calculating NCFs (use of S-transform (Baig et al. 2009; Hadziioannou et al. 2011), phase cross-correlation (Schimmel et al. 2011), boot-strap resampling (Liu et al. 2016), curvelet de-noising filter (Stehly et al. 2011) or singular value decomposition based Wiener filters (Hadziioannou et al. 2011; Moreau et al. 2017)).

Recent approaches for the calculation of velocity variations, such as the Dynamic Time Warping (Mikesell et al. 2015) or the Wavelet Cross-Spectrum (Mao et al. 2020), need to be applied to real data from volcano monitoring network in order to compare their advantages and disadvantages with respect to classical methods. As explained earlier, the reliability of the AVV in reflecting real physical phenomena depends on the stability of the noise sources. To verify this condition, standard tools, such as spectrogram, correlogram, correlation coefficient between reference and current NCFs,

should be widely used. The introduction of new procedures and the use of quality criteria would also be useful.

5.4 The Use of CWI for Volcano Monitoring and Eruption Forecasting

The modifications of NCF waveforms can result from perturbations of the seismic velocity and/or the structure of the medium. In a volcano, these perturbations can be related to magmatic and/or hydrothermal activity and thus can be considered as eruption precursors. However, as described in this chapter, a variety of processes can also produce perturbations of the medium and modify the NCFs. Therefore, it is important to identify the origin of any velocity variation, along with controlling that change against other observables, and to check the stability of the noise sources during the study period.

Volcanic tremor in particular can hamper seismic interferometry applications when it is not stationary (Gómez-García et al. 2018). In such cases, any change can leak into NCFs and produce unreliable AVV. It is advisable to regard tremor as a complication unless the stability of the tremor source, and corresponding NCFs, can be verified. Therefore, it is recommended to compute spectrograms, power spectral density or spectral coherence alongside AVV. New techniques that can assess similarity in NCFs (without a reference NCF) can also be useful towards determining the reliability of AVV when tremor is present (Yates et al. 2023). In the case where the sources of seismic noise are not stationary and when numerous events with similar waveforms are detected, CWI using multiplets can generate important complementary information on the volcanic processes (Budi-Santoso and Lesage 2016; Hotovec-Ellis et al. 2022). In addition, meteorological conditions can cause large changes in velocity. In regions with a strong rainy season, they can completely obscure AVV of volcanic origin. Likewise, snow cover induces large changes. At least two years of relatively continuous data are recommended to characterize background variations.

From the preceding discussion, it results that, although it can be an interesting and useful observation, AVV should not be used alone to evaluate the state of a volcano. Instead, the joint interpretation of the seismic activity, ground deformation and velocity variations would be very helpful. In addition, the analysis and comparison of many study cases are necessary to gain experience and to constrain interpretative models. Successes are important to analyse, but reports of lack of velocity changes are equally important. For example, dome collapses appear hard to track with seismic interferometry (Baptie 2010; Lesage et al. 2018a). Studies exploring several systems with the same set of parameters are desirable as done with tremor (Ardid et al. 2022). They could reveal common patterns or dissimilarities.

5.5 Physical Processes Related with Velocity Variations

Section 4 of this chapter presents a large variety of physical processes that can produce velocity changes. Other mechanisms must also be considered in some cases. For example, Bennington et al. (2021) suggested that thermal compaction of cooling lava flows induces long term seismic velocity increase.

Some mechanisms are still not well-understood and more research in this field is required to improve the interpretation of the observations. Complementary studies of rock mechanics based on laboratory experiments are necessary to better understand the behaviour of volcanic rocks and the relationship between their seismic velocities on one hand and stress and strain variations, pore pressure, distribution of crack orientations, damaging and rupture on the other hand (Fortin et al. 2011; Li et al. 2019). More investigation on the non-linear behaviour of pyroclastic granular material and on the corresponding slow dynamics (Johnson and Jia 2005; Johnson and Sutin 2005) would help understanding the velocity drops observed during strong earthquakes (Battaglia et al. 2012; Lesage et al. 2014; Machacca et al. 2019; Yates et al. 2019).

The value of the mean free path is required in the calculation of the sensitivity kernels (Eq. 28) and the location of perturbations (Obermann et al. 2013b). However, there are still very few estimations of this parameter in the literature (Prudencio et al. 2013a, b, 2015, 2017a, b) and the published values range from 100 to 4000 m (Table 1). It would be useful to get much more estimations of the mean free path at many volcanoes, to compare the different methods used and to evaluate the possible dependence on frequency and depth.

Many papers have reported velocity variations before eruptive activity, with both decreases and increases of velocity observed depending on the selected station pair (Budi Santoso et al. 2016). The development and application of analytical and numerical models of pressure variation in the plumbing or hydrothermal systems are necessary to decipher these complex patterns of AVV (e.g., Hotovec-Ellis et al. 2022; Muzellec et al. 2023).

This chapter has presented the principles of the coda wave interferometry, its main applications in volcanology, and the cautions required in interpreting the observations. The recent developments described here are very promising for highlighting subtle physical processes in active volcanoes and for providing new and efficient tools for monitoring and eruption forecasting. However, much investigation is required both on methodological and theoretical studies. Thus, this young field of research is expected to remain very active in the coming years.

Acknowledgements We thank Michel Campillo and Jean-Luc Got for discussions that helped clarifying several theoretical points. We also acknowledge the two reviewers who helped improving the manuscript of this chapter.

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The Use of Infrasound in Volcano Monitoring

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Abstract

Monitoring volcanoes is not limited to forecasting the onset of an eruption, but also includes confirmation of the occurrence of volcanic activity. In this chapter we will cover how infrasound, that is sound below human hearing, can be used as a monitoring tool. It is important to note that infrasound records atmospheric pressure perturbations and, as such, it requires coupling between its source and the atmosphere. Explosions are intuitive to understand; they produce audible acoustic energy, but also waves at lower frequencies below the audible range. This infrasound can be recorded instrumentally. Beyond explosion there is a broad range of volcanic activity that can be identified, located, tracked, or characterised using

acoustic records. Since infrasound attenuation is relatively low, compared to seismic waves, it can be recorded at distances ranging from few kilometres (local) to thousands of kilometres away from the source (global). This chapter will describe how infrasound is used to monitor volcanic activity.

1 Introduction

Volcanic activity releases energy both into the ground, as seismic waves, and in the atmosphere in the form of acoustic waves. The acoustic wavefield radiated by volcanoes is predominantly composed of low-frequency waves in the infrasound band, below 20 Hz, that can be used to detect, locate, and characterize volcanic activity, and to quantify eruptions (Braun and Ripepe 1993; Campus 2006; De Angelis et al. 2019; Dibble et al. 1984; Goerke et al. 1965; Johnson 2019; Johnson and Ripepe 2011; Kamo 1994; Mauk 1983; Matoza and Roman 2022; Okada et al. 1990; Ritsema 1980; Tahira et al. 1996; Wilson and Forbes 1969; Watson et al. 2022b). Infrasound travels at the speed of sound, approximately between 310 and 350 m/s, with a nominal value of 343 m/s at 20 °C, and its propagation is mainly controlled by the structure and properties of the atmosphere (Drob et al. 2003; Evers and Haak 2009).

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The interest in using infrasound to monitor volcanic eruptions originated in 1883 when a global network of barometers recorded acoustic waves from the large eruption of Krakatau, showing the potential for these waves to travel very large distances with comparatively low attenuation. Both the 1883 Krakatau, and the 2022 Hunga Tonga eruptions produced atmospheric waves that circled the globe at least 3 times with up to 7 arrivals recorded globally (Matoza et al. 2022; Scott 1883).

Starting from the early 1950s infrasound was also adopted as a monitoring tool for nuclear testing in an effort to monitor the proliferation of nuclear weapons worldwide. In the late 1990s the International Monitoring System, IMS, was created, following the establishment of the Comprehensive Nuclear-Test-Ban Treaty (CTBTO 2024). The IMS today includes, among many other geophysical instruments, 60 infrasound arrays located in various points on the globe designed to detect a 1 kiloton TNT or greater equivalent atmospheric explosion anywhere on Earth (Christie and Campus 2010). The development of the IMS has driven advancements in infrasound data processing beyond nuclear test detection, creating new opportunities for global monitoring of volcanic eruptions. Over the past three decades infrasound has become increasingly established as a tool for volcano monitoring; many volcanoes around the world are instrumented with at least one microphone, or can be monitored using sensors within regional or global scale networks such as the IMS.

Infrasound sensors are sensitive to pressure changes into the atmosphere, and therefore are not typically used to forecast the onset of eruptions, but to detect, characterise and track ongoing or changing volcanic activity. In order to produce an observable pressure perturbation, the acoustic source must be coupled to the atmosphere. At volcanoes, such coupling could be generated by direct interaction of the source with the atmosphere, or via the coupling between ground vibrations and the atmosphere, including those produced by shallow subsurface processes, for example, Matoza et al. 2009,

demonstrated that long-period seismic events could be associated with the generation of infrasound.

The advantage of Infrasound, in volcano monitoring, is that it can provide information about different types of surface activity (e.g., degassing, explosions, lahars, pyroclastic density currents; some illustrated in Fig. 1) even when no other direct observations can be made due to factors such as limited visibility (night-time or poor weather conditions), absence of direct line-of-sight, or remote location of the volcano.

In this chapter we will briefly illustrate examples of real-time application of infrasound to monitoring a range of signals from small events occurring on the flank of volcanoes, to larger explosions that could be recorded at much larger, and safer, distances.

2 Infrasound Sensors, Style of Deployment and Processing

2.1 Sensors and Noise

A range of sensors are used to record time series of variations of atmospheric pressure induced by volcanic activity. Acoustic waves are recorded, in the infrasound frequency band (0.01–20 Hz), by barometers, high-fidelity micro-barometers and lower cost sensors based on Micro Electro Mechanical Systems technology. The most capable of these sensors can record signals with amplitudes as low as just a few mPa and as high as a few thousand Pa. Sensor's sensitivity should be chosen according to the signal of interest; similarly the type of installation and site conditions can represent limiting factors in detecting a signal of interest. Even though there are a variety of potential noise sources in volcano infrasound (Matoza et al. 2013b, 2019), wind is the most common. The most suitable location for an infrasound sensor is in a heavily wooded area; vegetation acts as a natural filter to reduce wind noise (Garcés et al. 2003; Hedlin et al. 2002; Raspé et al. 2013); alternatively there are



Fig. 1 Examples of volcanic processes producing infrasound, in clockwise order, degassing, explosive eruption, pyroclastic density current

installation strategies that allow reducing signal deterioration using appropriately designed noise reduction systems (Raspet et al. 2013; Walker and Hedlin 2010). Beyond wind, other common natural sources of noise are thunderstorms and surf, which is dominant for stations located in coastal areas (Christie and Campus 2010). A well identified global source of infrasound noise is the microbarom (0.1–0.5 Hz), generated at the ocean/atmosphere interface (Bowman et al.

2005; Le Pichon et al. 2005). Since this source is ever present, though varying in location and amplitude, it is a good quality check on array-type installation (Garcés et al. 2009; Hupe et al. 2022).

As with most geophysical measurements, infrasound records a variety of anthropogenic sources such as aviation (e.g., helicopters), motor vehicle traffic, rockets, mining and quarry explosions, chemical explosions, industrial

sources, wind farms, and more. The quality of the signal, and hence the potential to monitor activity of any site at a given level, is strongly site specific. Each infrasound station will have a unique noise profile based on its installation (sensor, location, wind noise reduction system, and nearby noise sources). Therefore, site selection is an important aspect of any installation.

2.2 Style of Deployment and Data Processing

Microphones can be deployed in different configurations including single-station, networks, or arrays (Fig. 2). These styles of deployment differ for the number and type of microphones employed, spatial separation between sensors, and their specific monitoring task.

Single-stations and networks are the most common type of deployment for detecting and tracking volcanic activity at local distances. These are commonly co-located with seismic stations (Arrowsmith et al. 2010; Braun and Ripepe 1993; Dibble et al. 1984; Goto and Johnson 2011; Green and Neuberg 2005; Iguchi et al. 2013; Johnson et al. 2009; Okada et al. 1990; Yamasato 1997). In contrast, infrasound arrays are employed for detection and tracking of volcanic activity at distances from local, order of a few to 15–20 kms (e.g., De Angelis et al. 2020; Garces et al. 2009; Matoza et al. 2007; Ripepe and Marchetti 2002; Thelen and Cooper 2015) to regional, order of up to few hundred kilometres (e.g., Perttu et al. 2020b; Tailpied et al. 2013) and even global, up to several thousand kilometres (e.g., Dabrowa et al. 2011; Matoza et al. 2011a, 2022). Within networks, microphones

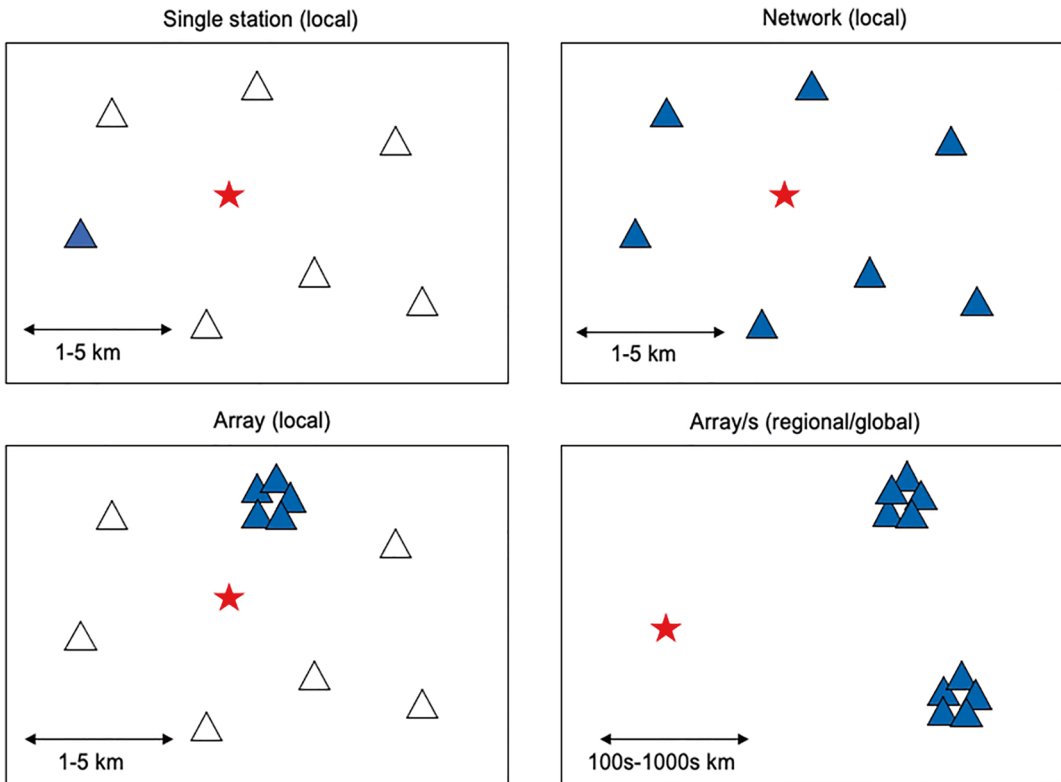


Fig. 2 Schematics of deployment design types. Top: single station and network. Bottom array both local and regional/global

are deployed at separate sites in order to achieve the best possible azimuthal coverage around one or multiple active volcanic vents. Arrays are clusters of multiple sensors installed at a single location where the geometry of the array is controlled by the source-site distance and the wavelength of the signal being investigated. Network and array data are processed with different methods and deliver different products.

Array processing assumes waveform coherence across the array, while network processing considers data from each sensor uncorrelated. Infrasound array processing is frequently based on the plane-wave assumption and provides a time series of direction of arrival, DOA, or back azimuth, slowness or apparent velocity, and power of the wavefront across the array at different frequencies. The most used algorithms for infrasound array data processing include: (i) least-square beamforming via inversion of travel-time delays between each pair of sensors within the array (e.g., Bishop et al. 2020; De Angelis et al. 2020; Szuberla et al. 2006); (ii) frequency-wavenumber analysis to perform a simultaneous search over a grid of candidate slowness and DOA values to find the parameter

combination that produces the highest power of the summed signal across the array (e.g., Rost and Thomas 2002); (iii) Progressive Multi-Channel Correlation, PMCC, based on a closure relation between any three sensors within an array across multiple narrow frequency bands (e.g., Cansi 1995). An example of the typical output of infrasound array processing using least-square beamforming, including uncertainty estimates on DOA and velocity measurements (De Angelis et al. 2020) is shown in Fig. 3.

In contrast to array processing, infrasound network processing provides an absolute source location. Network data processing is generally based on grid-search methods (e.g., Fee et al. 2021; Kim and Lees 2014, 2015; Sanderson et al. 2020; Walker et al. 2010). These algorithms leverage theoretical travel time information between candidate sources (i.e., the grid points) and each sensor within the network to search for the grid point that maximizes a characteristic function such as the stack of waveform envelopes across the network (Fig. 4b, e.g., Fee et al. 2021) or the network semblance (Fig. 4a; e.g., Cannata et al. 2009; Jones and Johnson 2011; Ripepe and Marchetti 2002).

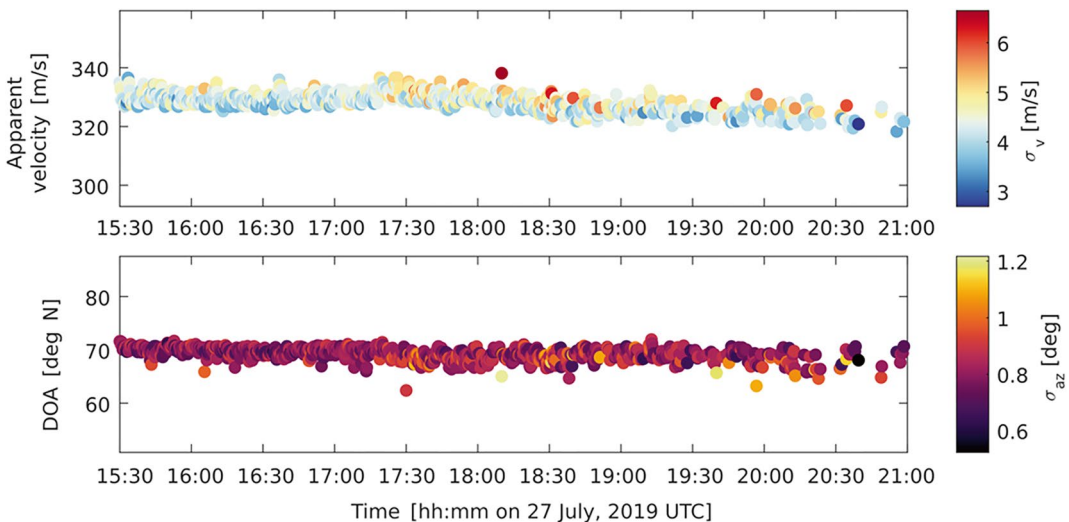


Fig. 3 Example of local array location at Etna, Italy, using the slowness inversion method with uncertainty estimates (source code and data available in De Angelis et al. 2020)

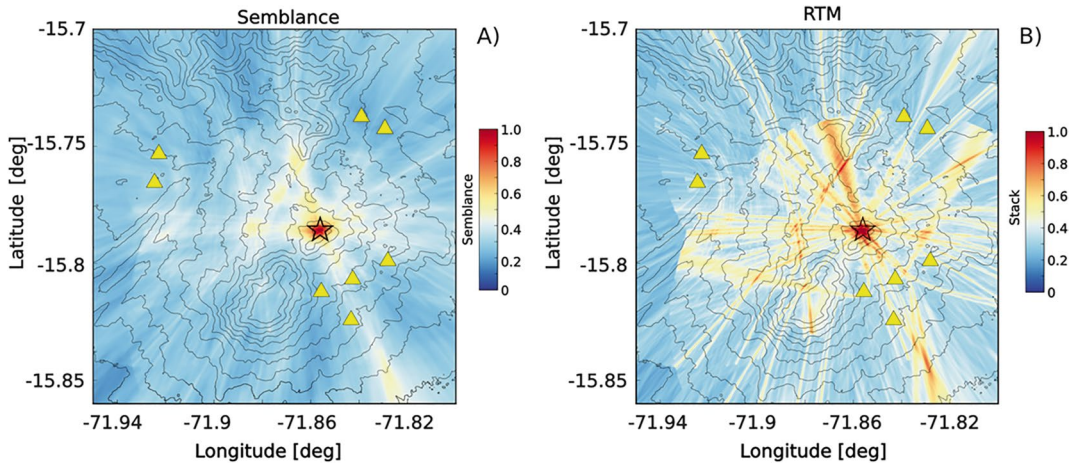


Fig. 4 Infrasound network locations and grid search results of an explosion at Sabancaya volcano, Peru, using two different methods. **a** Using semblance (e.g., Cannata

et al. 2009; Ripepe and Marchetti 2002) and **b** using reverse time migration (e.g., Fee et al. 2021)

3 Local Monitoring

A variety of infrasound is recorded at local distances from active volcanic vents, spanning a range of frequencies, amplitudes, and durations. Typical volcano infrasound ranges from short transients (durations of few to ten of seconds), such as the waveforms generated by Strombolian or Vulcanian-style explosions, to longer duration signals associated with a broad spectrum of activity from sustained degassing to syn-eruptive to acoustic tremor, or from surficial events (e.g., pyroclastic flows, lahars), as well as sustained eruptions. Over the past two decades the use of infrasound has become commonplace in volcano monitoring with many observatories operating small local networks of microphones in real-time. At a minimum, local microphone networks and arrays allow efficient and reliable detection and location of acoustic sources associated with volcanic unrest. More recently several studies have demonstrated the potential of infrasound for additional operational use such as the assessment of eruption source parameters (e.g., eruption rates) in real- or near real-time. At open-vent volcanoes local infrasound arrays have been shown to hold great promise for the implementation of volcano early warning

systems (De Angelis et al. 2020; Fee and Garcés 2007; Matoza et al. 2007, 2010; Ripepe et al. 2010).

3.1 Eruption Source Parameters and Plume Height on Local Sensors

Infrasound, in addition to source detection and localization can be used for the calculation of eruption source parameters including exit velocity, flux, and plume height. This is generally accomplished by converting the infrasound data into acoustic power following the pioneering work of Woulff and McGetchin (1976) based on Lighthill (1952, 1963). Early work in applying this methodology was focused on the source volume estimation of Strombolian style eruptions; (Johnson and Aster 2005; Vergnolle and Brandeis 1994, 1996; Vergnolle et al. 1996) however, it now has been expanded to be applicable to a variety of eruption styles. Based on the initial work by Woulff and McGetchin (1976) several studies have now established a methodology to convert infrasound data from a pressure time series into an estimated of exit velocity that can be converted to volume flux

(assuming geometry of the vent), and from there plume height estimation (Vergnolle and Caplan-Auerbach 2006; Caplan-Auerbach et al. 2010; De Angelis et al. 2023; Lamb et al. 2015; Matoza et al. 2013a; Ripepe et al. 2013; Perttu et al. 2020b). This method converts the data from a pressure signal to acoustic power and from there the relationship between the radiative pattern (monopole, dipole, quadrupole) and acoustic power is used to derive the exit velocity at the vent. Fee et al. (2010) uses acoustic power to determine plume height based on an empirical relationship established for Tungurahua volcano. However, it should be noted that this methodology as currently stands has significant uncertainties associated with it. For example, when extending to regional, or global estimate, one major uncertainty comes from the conversion from volumetric flux (gas and particles) to the dense rock equivalent needed for several of the plume methods (Perttu et al. 2020b), and another comes from the complexity of acoustic sources (Matoza et al. 2013a). While temporary operational applications of infrasound for eruption source parameters have been used, to the best of our knowledge there are, no real-time operational tools for automated plume height estimate at the time of this writing. Further research is required to refine this methodology for real-time operational use.

More recently several studies (Diaz-Moreno et al. 2019; Fee et al. 2016; Iezzi et al. 2022; Kim et al. 2015) have explored full infrasound waveform inversion, akin to seismic moment tensor inversion, to retrieve the time history of volume flow rate associated with volcanic explosions. These methods exploit 3D numerical Green's Functions (or the impulse response of the atmosphere) to invert waveform data for the acoustic source mechanism. In these inversion schemes the acoustic source is represented as a multipole series, typically the combination of a monopole term, representing the net flow of mass into the atmosphere, and a dipole that represents momentum changes within the flow not associated with the introduction of new fluid. Higher order terms in the multipole representation of the acoustic source are usually

neglected as their estimate through inversion would require waveform data that are not readily available such as, for example, acoustic measurements in the atmosphere (Iezzi et al. 2019a). Waveform inversion using 3D numerical Green's Functions has the advantage of accounting for the effects of topography and the atmosphere on the propagation of the acoustic wavefield, but it comes at a comparatively high computational cost, as signal frequency increases. Furthermore, recent work by Lacanna and Ripepe (2020) using 3D numerical modelling demonstrated that the strong acoustic impedance contrast at the interface between volcanic vents and the atmosphere can cause most of the acoustic wave energy (between approximately 50 and 90%) to be reflected back into the conduit. Finally, Lacanna and Ripepe (2020) suggest that the volume flow inside the conduit can be calculated, assuming a monopole source, from the recorded infrasound waveforms after applying corrections for the reflectance at the vent-atmosphere interface, and the effect of topographic scattering represented by the acoustic insertion loss. De Angelis et al. (2023) applied this workflow at Mt. Etna validating the infrasound-derived measurement with independent thermal infrared and ground-based radar data.

3.2 Mass Movement (PDC, Lahar, Rockfall, Debris and Snow Avalanches)

In addition to eruption signals, infrasound installed locally at volcanoes can record a variety of mass movement signals. Surficial mass movement on volcanoes such as rockfalls, debris avalanches, lahars, sector collapses, and pyroclastic density currents are some of the deadliest volcanic hazards related to volcanic activities (Tanguy et al. 1998). The acoustic source mechanisms of these types of events are not well understood owing to their complexity compared, for example, to an explosion signal. These signals may also be easily mistaken for wind noise due to their emergent and sustained characteristics (Allstadt et al. 2018). However,

these signals are well represented within monitoring datasets. They are typically associated with broadband signatures and event characterization may be dependent on the type of sensor used as their frequency content can extend into the audible range (>20 Hz) or, as in the case of a rockfall described by Moran et al. (2008), below 0.02 Hz. For additional details on the seismo-acoustic characteristics of each type of mass movement we refer the reader to a comprehensive review paper by Allstadt et al. (2018).

3.2.1 Rockfalls and Debris Avalanches

Rockfalls and debris avalanches range in volume, from small to large, composition, and type of movement. While there are few reports in the literature of infrasound from debris avalanches (Allstadt et al. 2018; Marchetti et al. 2019) rockfalls are common in monitoring data (Allstadt et al. 2018; Johnson and Ronan 2015; Thelen and Cooper 2015). Rockfalls tend to have a more impulsive signal but can exhibit complex waveforms with acoustic signals generated from different parts of the rockfall. The signal generated by the bulk displacement of air is typically lower frequency, <1 Hz, while impacts,

within the rockfall and on the ground, tend to be recorded at higher frequencies, >1 Hz (see Fig. 5 for example). The waveforms and spectral characteristics of rockfalls are distinct from those associated, for example, with degassing and explosions (Allstadt et al. 2018). Rockfalls are one of the smallest type of volume mass movements generating infrasound, but the most common in occurrence (Allstadt et al. 2018).

3.2.2 Snow Avalanches

On high-latitude and snow-covered volcanoes, snow avalanches can be frequent. Infrasound from snow avalanches is thought to be generated by the turbulent motion at the flow front and can be recorded from tens to hundreds of kms from the source (Allstadt et al. 2018). Infrasound has been proposed for and used to monitor for snow avalanches in the USA and Europe (Fedorov et al. 2021; Johnson et al. 2021; Kogelnig et al. 2011; Marchetti et al. 2015, 2020; Scott et al. 2007; Schimmel et al. 2017; Olivieri et al. 2011). Due to the known location of prolific avalanche channels, array processing can be used for localization of events. Array data show that snow avalanche signals are characterized

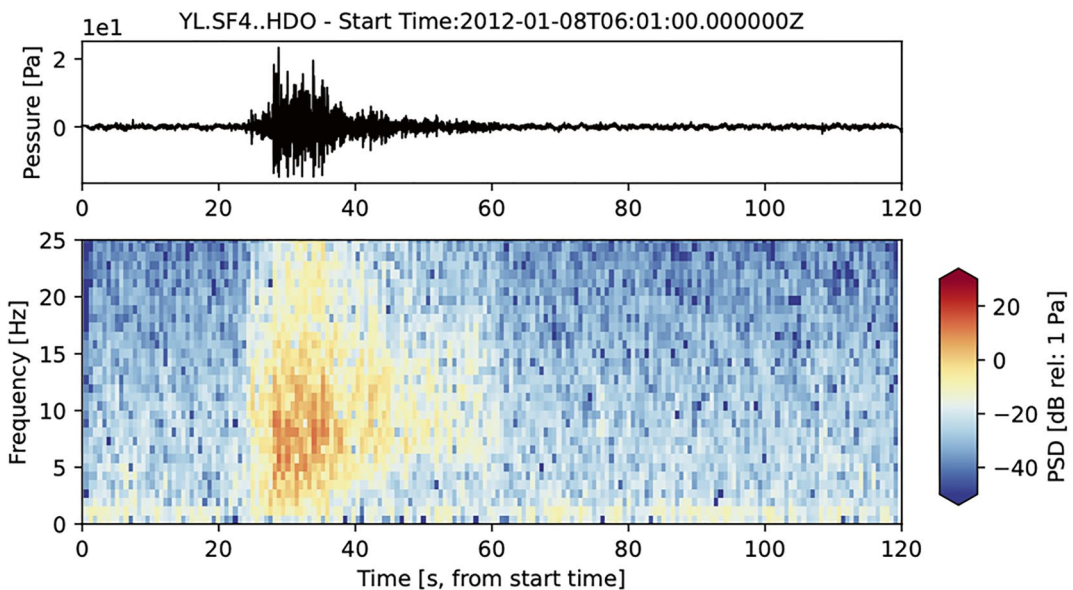


Fig. 5 Example of rockfall infrasound recorded at the Santiaguito lava dome complex. Instrument located at ~ 600 m from the active Caliente lava dome

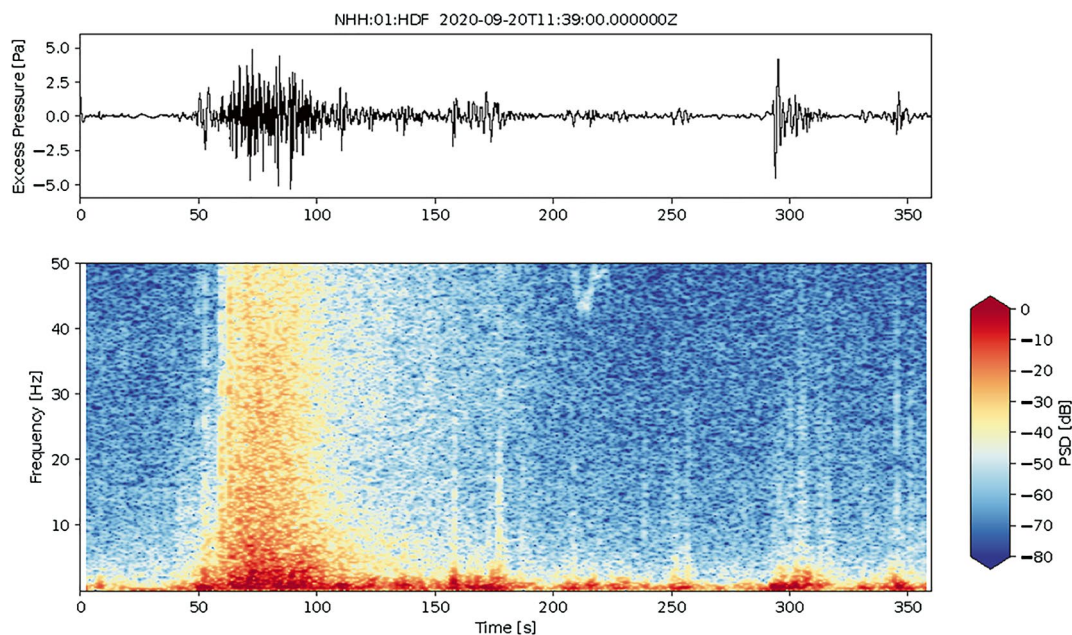


Fig. 6 Example of snow avalanche's generated infrasound recorded along the Milford road, New Zealand (Aetearoa). Instrument array located within 1 km from the source (Watsons et al. 2022a)

by clear back azimuth variations and changes in apparent velocity (Marchetti et al. 2020; Watsons et al. 2022a) (Fig. 6).

3.2.3 Lahars

Lahars, or fluidized debris flows, originating on volcanoes can occur during an eruption, as well as outside of eruptive activity when loose material could be remobilized. Lahars are not associated with any obvious warning sign and the ability to quickly locate and identify them is of prime importance. Infrasound has been used as a tool to monitor these events on volcanoes (Hurlimann et al. 2019; Sanderson et al. 2021). Infrasound lahar monitoring systems are typically designed employing one or multiple arrays. This allows focussing on known areas for signal sources (i.e., known lahar channels) and continuous tracking of their movement (e.g., Bosa et al. 2021; Johnson and Palma 2015). Signals from lahars are typically emergent and broadband, both in the seismic and acoustic records, with durations of tens of minutes to hours. The characteristics of the signal, including amplitude, and duration depend on flow

regime as well as the distance between the lahar and the recording sensors (see Fig. 7 for examples). In a pilot study at Mount Adams in the Cascades, Sanderson et al. (2021) state that any lahar signal is expected to be either emergent or impulsive in onset depending on the source, with most of the energy concentrated between 1–10 Hz, a varying back azimuth in the array processing results associated to its propagation, and have a reduced pressure at 1 km from the source from 1–110 Pa depending on the size of event.

3.2.4 Pyroclastic Density Currents

There have been multiple studies on the infrasound produced by Pyroclastic Density Current, PDC, mostly focused on Mount Unzen, Japan, and Soufriere Hills volcano, Montserrat (Delle Donne et al. 2014; Oshima and Maekawa 2001; Ripepe et al. 2009, 2010; Yamasato 1997). In the pioneering work on PDC infrasound at Mount Unzen, PDCs were observed with a seismo-acoustic network comprising short and long-period seismometers, two types of low frequency microphone, and visual data provided by

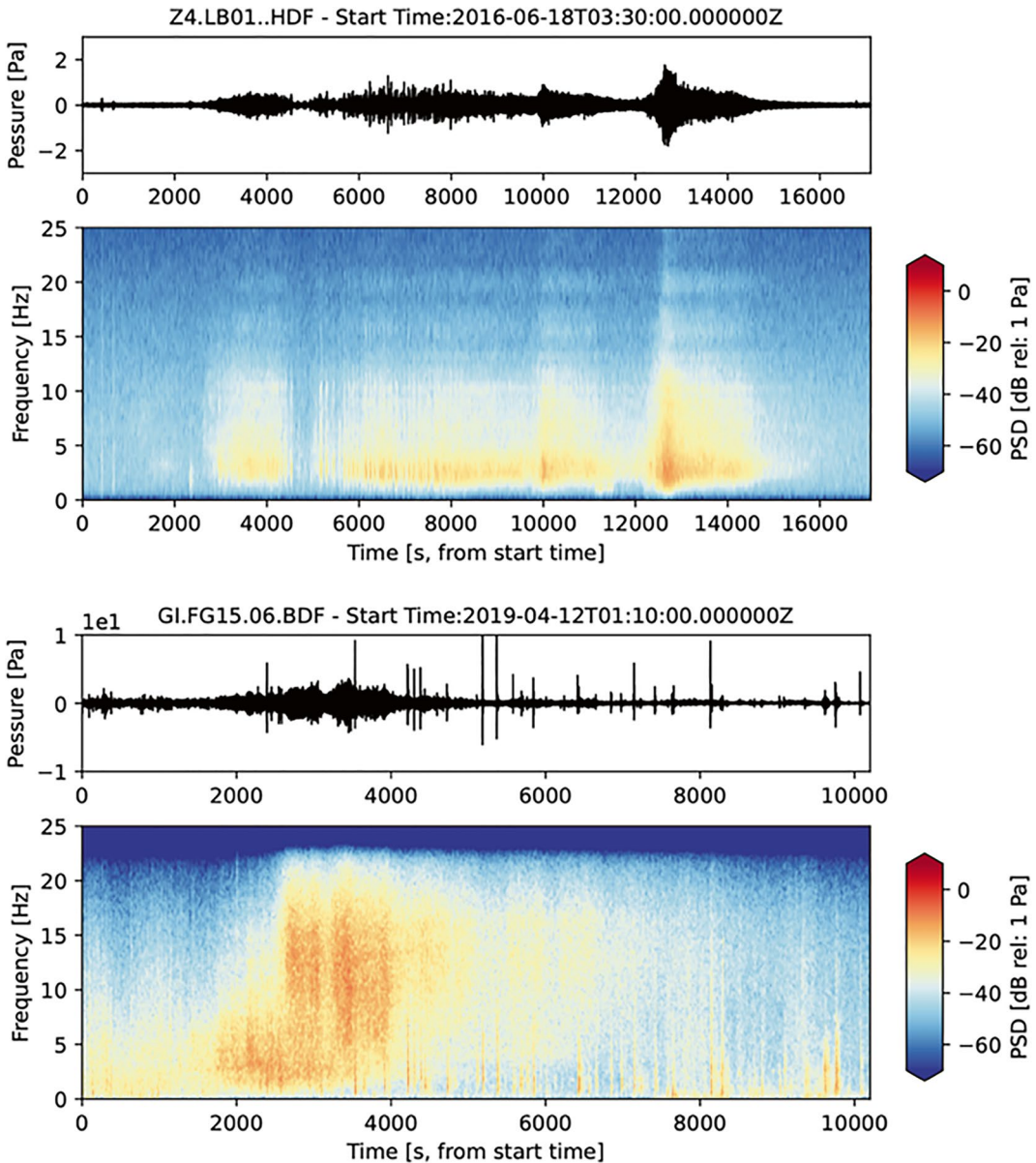


Fig. 7 Examples of lahars recorded at Santiaguito (top) and Fuego (bottom). The two records show variability of lahar infrasound. Instrument located at 2–3 kms and 5–7 kms from the active channel, respectively

a camera at one of the stations (Yamasato et al. 1993; Yamasato 1997). One of the key observations of this early work was the presence of a Doppler shift in the infrasound signals due to the moving source of the PDC. At Soufriere Hills volcano in Montserrat an array configuration was used to track PDCs and map the runout and

flow velocities (Ripepe et al. 2010). Infrasound produced by PDCs is broadband in character and the source is likely linked to turbulent processes (Fee and Matoza 2013). However, these signals may be difficult to isolate from the concurrent volcanic activity (see Fig. 8 for example).

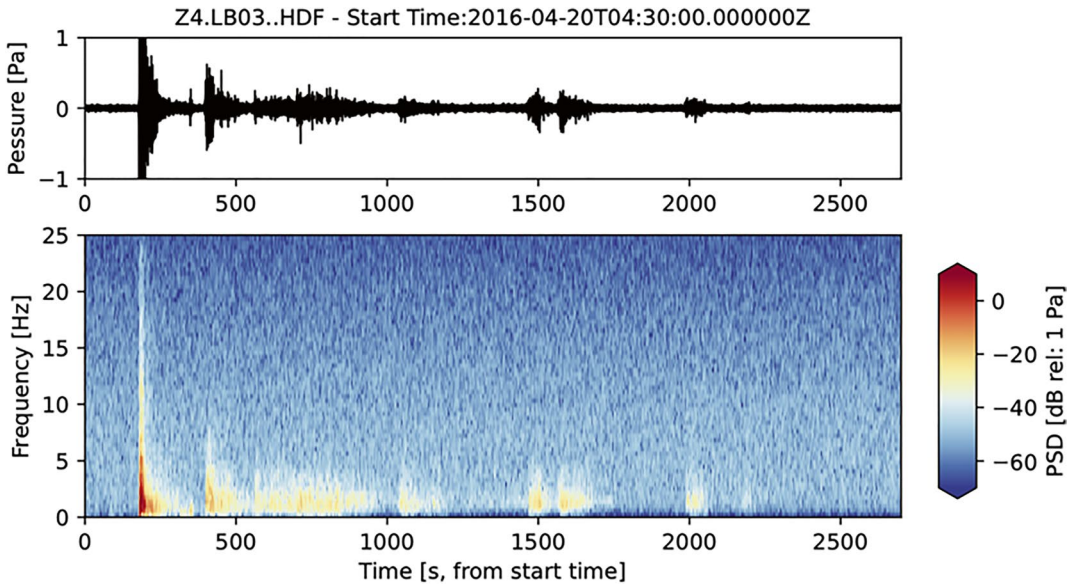


Fig. 8 Example of an explosion followed by a sequence of Pyroclastic density currents from Santiaguito. Instrument located at ~ 2.5 km from the source. The vertical axis of the waveform plot (top) is scaled between -1

and 1 Pa to show the smaller amplitude signal from the PDC. PDC infrasound frequencies are relatively low, consistent with signals recorded at Soufriere hills volcano, Montserrat (Ripepe et al. 2009)

3.3 Lava Flows, Lava Fountains, and Fissures

Lava flows, lava fountains, and lava lakes tend to produce broadband, tremor-like, signals (Fee and Matoza 2013). An example of periodic lava fountaining recorded during the 2021 Fagradalsfjall eruption, Iceland (Lamb et al. 2022), is shown in Fig. 9. During effusive eruptions, when a fissure or an eruptive vent has opened, knowing where the location of the activity is, is important for managing the safety of those nearby. Array processing of infrasound data has been successfully used to constrain the location of fissures and active vents during several effusive eruptions (e.g., Badger et al. 2012; Thelen and Cooper 2015).

large enough. Here we will define “remote monitoring” as monitoring that could be performed from a safe distance with no risk of losing the integrity of the sensors, nor data transmission, due to volcanic hazard. The type of information that can be obtained remotely ranges from the location of the activity, to the estimation of eruption source parameters. Those will be described in the following sections.

4.1 Monitoring for Eruptions

Regional and global monitoring are made possible by the use of the International Monitoring Systems deployed by the CTBTO. The availability of these data ranges from fully open and accessible via the Incorporated Research Institutions for Seismology, to restricted and available upon request or through established relationships within the IMS/CTBTO framework. This backbone of remote monitoring is complemented by other regional stations and sensors (Iezzi et al. 2019b; Matoza et al. 2019; Marchetti et al. 2019; Taisne et al. 2019;

4 Regional and Global Monitoring

Infrasound monitoring of volcanic activity can be performed locally, as discussed in the previous section, or remotely if the energy released is

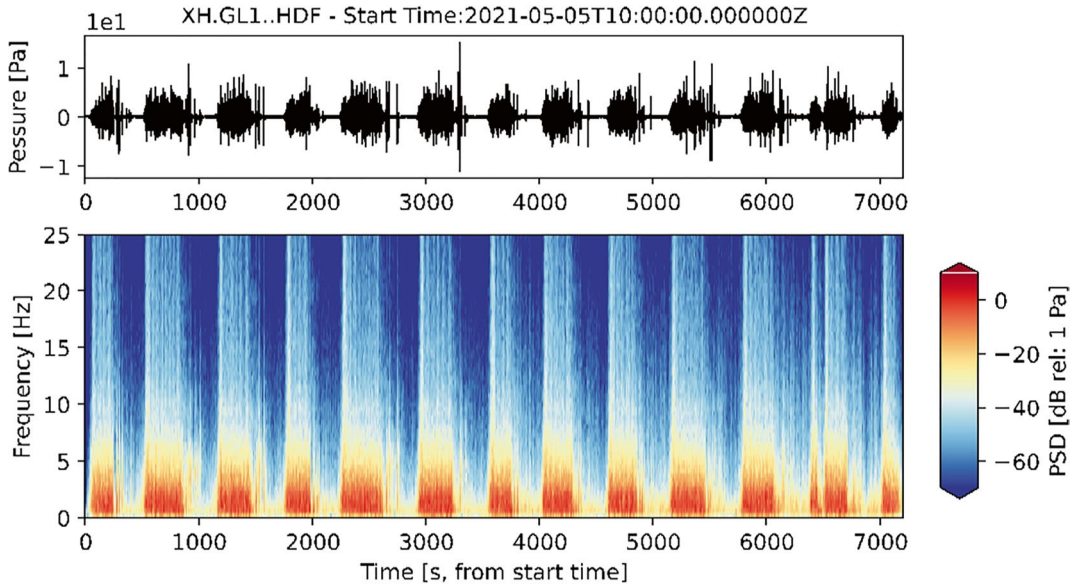


Fig. 9 Example of acoustic recording associated with lava fountaining during the 2021 Fagradalsfjall eruption, Iceland. Instrument located at ~ 1 km from the source

Perttu et al. 2023). The 2022 eruption of Hunga volcano is a modern example of large-scale explosion with data recorded on a range of national research networks, and the IMS network (Matoza et al. 2022). While this is an extreme example, and the largest volcanic signal recorded by the IMS network, long-lasting eruptions of moderate amplitude can also be recorded and located, which is valuable to track activity from isolated volcanoes (Matoza et al. 2017). Remote monitoring using infrasound is limited to the ability of the sensor to record the energy received, which depends on the intensity of the signal at the source, its attenuation in the atmosphere before reaching the sensors and the noise level at the sensors (Dabrowa et al. 2011; Tailpied et al. 2021; Taisne et al. 2019). This is aided using array processing algorithms like PMCC (see Fig. 10). However, closer, or louder signals or sources with similar back-azimuth may mask the signal (Taisne et al. 2019). Finally, infrasound propagation velocity is a limiting factor in terms of lag time between the event of interest and the time at which the signal can be recorded. Typical latencies are between 47 and 54 min per 1,000 kms. To offset

this weakness in remote monitoring with infrasound, the installation of more regional arrays would be required. This would improve both the scale range of events that could potentially be detected, as well as the time latency at which the information is recorded. The distance and number of regional arrays should be motivated by the desired delay time thresholds for the region. It is important to understand these limitations before using regional or global infrasound monitoring as an operational solution for determining eruption source parameters like plume height and duration.

4.2 Remote Eruptions Source Parameter Estimation

Perttu et al. (2020a) presented a methodology expanding on the methods used for local infrasound source parameter estimation (Sect. 3.1) for a regional to global range. The main difference between local infrasound and regional to global infrasound is that with increasing distance the complexity of the propagation and attenuation also increases. However, given that

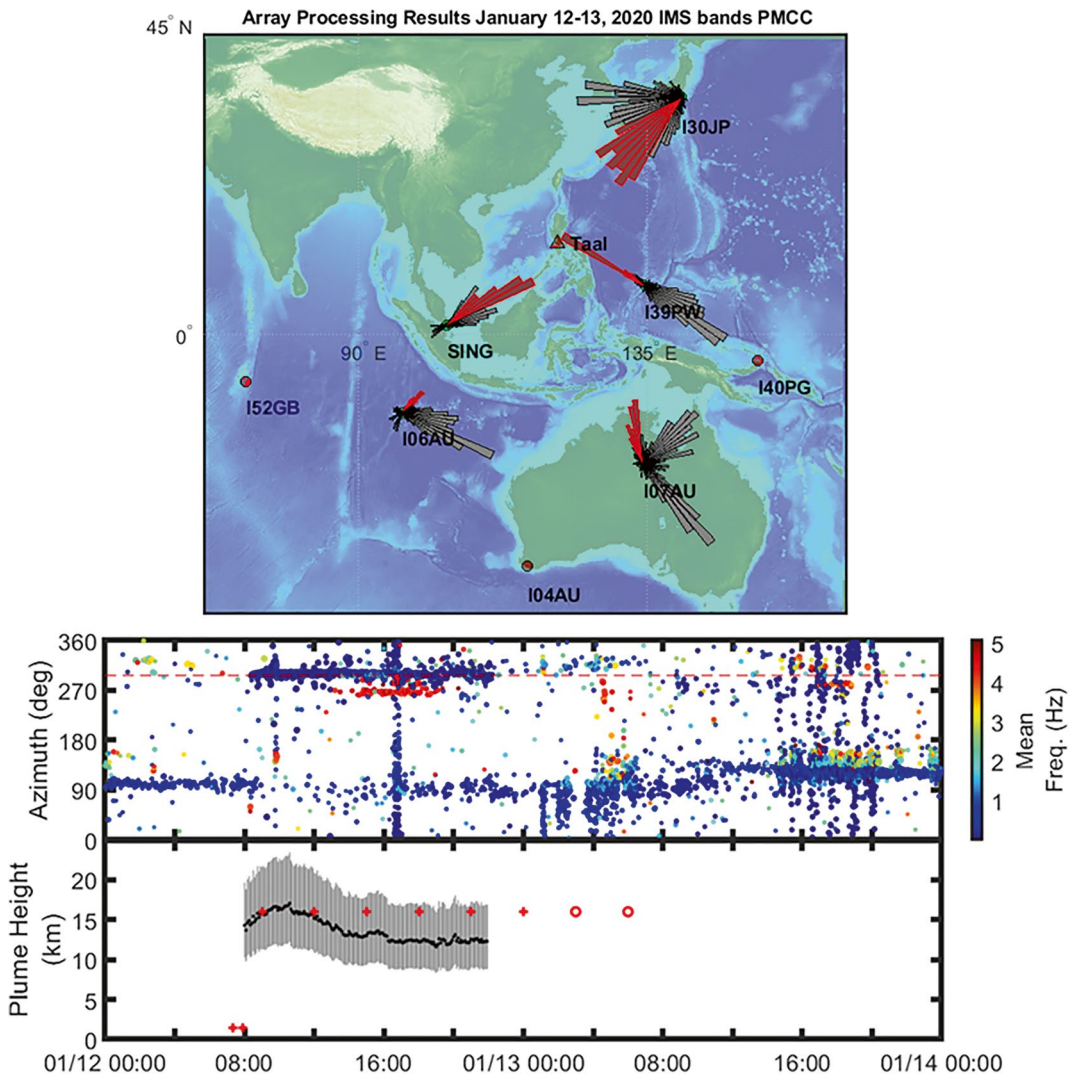


Fig. 10 Array processing results for the January 12, 2020, eruption of Taal volcano, Philippines. Results from the UTC days January 12th and 13th from the regional infrasound arrays using the PMCC (Cansi 1995) method. The map view representing the results in the direction of the volcano are highlighted red ± 15 degrees from the known back azimuth. The middle panel shows the array processing results from I39PW using PMCC. The back azimuth of the volcano is indicated by the red dashed

line. The bottom panel shows the calculated plume height estimate for the period of time with strong array processing results from the azimuth of the volcano. The range of results including uncertainties is plotted as a vertical bar with the results using the preferred set of assumptions is plotted as black dots. Reported plume heights are plotted in red. See Perttu et al. (2020a) for details on these assumptions and uncertainties

most attenuation modelling returns a reduced distance measurement, usually 1 km from the source, remote measurements can be back propagated to near the source and then the same methodologies used for local infrasound can be implemented. While there are several important

assumptions that need to be considered, this methodology was shown to provide a plume height within the range measured by satellite for multiple eruptions (see Fig. 10).

Other source parameters like duration and number of eruptions can also be extracted from

regional data. However, unlike with local data, the specific propagation path should be considered. There are several well-known examples of single explosions that have resulted in multiple infrasound detections due to different propagation paths (Ceranna et al. 2009; Pilger et al. 2021). Even though infrasound has relatively low attenuation allowing it to be detectable for long distances, propagation effects cannot be ignored in regional to global range detections. The explosion in Beirut in 2020 resulted in multiple pulses being recorded at some stations, even though there was only one explosion, due to the energy separating into multiple stratospheric propagation paths (Pilger et al. 2021). Something similar was observed for the flank collapse at Anak Krakatau in December 2018 (Perttu et al. 2020a).

While the path effect could smear the signal in time by producing multiple arrivals from a single impulsive event, duration of the activity at the source could still be extracted. The examples from Kelud, Anak Krakatau, Taal, Ulawun, and Raikoke (Caudron et al. 2015; McKee et al. 2021a, 2021b; Perttu et al. 2020b, 2023) demonstrated the potential to extract the duration of the intense phase of those eruptions.

5 Reflections and Future Directions

Infrasound arrays are already well established and widely used at all scales from local to regional—even globally for larger events. Future advances in array technology should now be focusing on improving noise reduction to lower detection thresholds and reducing uncertainties in event locations. Future research should further explore the use of multiple arrays to obtain absolute event locations from cross-beam methods (Matoza et al. 2011b, 2017, 2018; McKee et al. 2021a, b). At regional and global scales there is potential to exploit remote infrasound to reconstruct the time history of eruptions (e.g., their onset and duration) and to link the appearance of its waveforms to the dynamics

of volcanic ash injection and transport in the atmosphere (Perttu et al. 2023; Fee et al. 2010; Garcés et al. 2008; Matoza et al. 2011a).

Microphone networks installed locally on volcanoes are commonplace although there are still relatively few examples of infrasound real-time data processing being fully integrated into volcano monitoring systems (Ripepe et al. 2007). The most immediate use of local infrasound network data on volcanoes is for the detection and location of both explosions and other longer duration signals (e.g., Ripepe et al. 2018).

Ongoing research focuses strongly on improving our ability to exploit (local and regional) infrasound data to constrain eruption source parameters, which are key inputs into numerical models of atmospheric ash plume rise and transport used operationally for risk mitigation in the aviation industry. Recent works have focussed, with encouraging results, on the use of infrasound arrays to detect and track gravity driven flows such as lahars, pyroclastic density currents, debris flows, landslides and avalanches (Delle Donne et al. 2014; Johnson and Palma 2015; Sanderson et al. 2021; Toney et al. 2021).

In terms of monitoring strategy, it is important to consider: what is the biggest hazard that needs quick identification and characterisation? This would lead to answering some key questions during the planning phase of an infrasound installation and making strategic decisions on the type of installation that would best fit the needs. Are we interested in local sources with known origin, e.g., explosions from a single vent, or are we interested in monitoring mass-flows that could be taking place in different channels? In the former, a network of sensors, collocated with an existing seismic network for example, will be sufficient. While in the latter, 2 or 3 small aperture arrays would be needed to identify with a reasonable level of certainty the location and progression of the flow.

Each volcano is different and what works on one cannot always be transferred to another. The main difference to consider will be the local topography as it could act as a barrier to

constrain the achievable azimuthal coverage. However, limitations on installation location can also lead to issues with site noise and the minimum detectable activity to be recorded above it.

A similar philosophy will apply at the regional scale, what is the purpose of the installation? Monitoring of a known source from a safe distance, or monitoring multiple potential sources? How long could you afford to wait before getting the signal recorded and hence getting information on the source? What are the dominant wind patterns in the region of interest and how does it compare to the station direction and distance from the potential source of interest to have optimum recording of signal after propagating into the atmosphere?

6 Conclusion

Infrasound technology is becoming an integrated part of monitoring networks and used for confirmation of different types of activity taking place at the surface which interacts with the atmosphere. At the local level, infrasound can be used to confirm the intensity of an explosion, the occurrence of mass movements and their potential location, or the location of activity along an eruptive fissure. The fact that no direct observation is needed makes this technology the perfect complement when visual confirmation is not possible due to adverse weather or time of the day.

At a regional level infrasound has the potential to provide input parameters for other models by the derivation of maximum plume height, through empirical laws or numerical models, and duration of the intense phase of eruption. These important parameters must be combined with other metrics, such as mass loading and particle size distribution, to run ash dispersion modelling. The estimation of volcanic hazard based on remote monitoring requires assumptions and brings uncertainties associated with those assumptions. On the other hand, infrasound provides a real-time, independent, source of information, which might also be the only available at the time of eruption.

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Geochemical Monitoring of Volcanic Fluids in the Twenty-First Century

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Abstract

This chapter reviews the state-of-the-art of geochemical volcano monitoring techniques. We cover in-situ monitoring technologies that rely on sampling fluids (direct sampling) and on instrumental analysis of the composition of such fluids in real-time (remote sensing of volcanic fluids is covered elsewhere in this book). We first review key concepts and principles in the field, and then review the results of some selected case studies and applications. We cover the large variety of fluid categories emitted by volcanoes, in both the near-(crater fumaroles and lakes, and plumes) and far-(degassing soils, groundwaters)

fields. Our aim is to demonstrate the utility of measuring the chemistry of fluids released by volcanoes, and how these can help characterize volcano unrest, and eventually the increased likelihood of eruption. We conclude with a brief discussion of current challenges and knowledge gaps, and on future directions in geochemical monitoring.

1 Introduction

The geochemistry of fluids released by volcanoes (hereafter ‘volcanic fluids’) is central to modern volcano monitoring (Oppenheimer et al. 2014; Fischer and Chiodini 2015; Edmonds et al. 2021; Kern et al. 2022). Volcanic fluid emissions (e.g., hot fumaroles and plumes, hot pools, sparkling groundwater, crater lakes) have long attracted the attention of humans, but have for centuries been conceived as odorous, colorful but overall secondary manifestations of volcanism. The first quantitative determinations of the chemical composition of volcanic fluids began in the late XIX century (Jaggar 1940), but it was only in the 1970s (Matsuo 1975) that volcanic fluids started to be increasingly employed in monitoring volcanoes, and to aid in forecasting volcanic eruptions (Menyailov 1975).

In the modern view of active magmatic systems (Cashman et al. 2017), it is now universally accepted that magma-transported volatiles are

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key factors in volcanic processes. For example, volatiles play a role in controlling the degree of melting of the mantle source, and hence composition, rheology, and *liquidus* temperatures of the resulting melts (Dasgupta 2018)—these, in turn, govern buoyancy, and therefore whether magma will ascend (and at what rate) or stall (to be stored in magmatic reservoirs) when injected in the crust (Putirka 2017). Even more significantly, the gas bubbles that form during magma decompression and ascent are causal factors in pressurization of magma reservoirs (Huppert and Woods 2002; Parmigiani et al. 2016), and ultimately determine magma fragmentation during explosive eruptions (Gonnermann 2015). Such gas bubbles are also heavily implicated in the generation of a large variety of geophysical signals used to monitor volcanoes, including seismic tremor and LP/VLP seismicity (Shapiro et al., this book) and infrasound (Taisne et al., this book). By controlling magma compressibility, gases contribute to determining the extent of volcano deformation during the inflation/deflation cycles that precede/accompany volcanic eruptions (Voight et al. 2010).

Volcanic fluids are extremely attractive for volcano monitoring purposes. These fluids are the surface expression of gas bubbles separated from stored/ascending magma in the subsurface (Fig. 1). Magmas contain major (H_2O , CO_2 , S) and minor (halogens, nitrogen, noble gases) volatile components (Wallace et al. 2015), plus a variety of trace volatile species (Edmonds et al. 2018). These volatiles, while initially dissolved in the silicate melt at high pressure, partition into a separate gas phase at lower pressure (typically, in the upper mantle to crust) (Fig. 2) as their solubilities in melt decrease (Wallace et al. 2015; Papale et al. 2022). The bubbles that form during magmatic degassing are less dense than the silicate melts and can therefore escape (separately ascend) by buoyancy, and/or when a gas percolation/permeability threshold is reached (Rust and Cashman 2004; Oppenheimer et al. 2014; Edmonds and Wallace 2017). At least in principle, magma-sourced volcanic fluids are therefore expected to reach the surface long before magma, ultimately anticipating

volcanic eruptions. The ultimate goal of volcano geochemists is to capture this “telegram from the Earth interior” (Matsuo 1975) sent by soon-to-erupt magma, using measurement of the composition and flux of surface fluid emissions (Fig. 1).

Volcanic fluids can be emitted in a variety of forms (Edmonds 2021), including: (i) large atmospheric plumes released by erupting or passively degassing open-vent volcanoes (Fig. 1c; Carn et al. 2017; Aiuppa et al. 2019); (ii) from crater lakes (Fig. 1d; Pérez et al. 2011; Christenson et al. 2015); (iii) through the odorous fumaroles that punctuate the summits of closed-vent dormant volcanoes and calderas (Fig. 1e; Fischer and Chiodini 2015); (iv) in less perceptible, but occasionally massive form through soil diffuse emissions (Fig. 1f; Chiodini et al. 1998); and (v) as dissolved gases in volcanic groundwaters that eventually become effervescent upon atmospheric discharge at hot/cold springs and pools (Giggenbach 1997) (Fig. 1g). Geochemists have adapted their gas sensing techniques to capture the essence (composition, flux) of magmatic gas release through each of these emission types.

Traditionally, direct sampling of fumaroles, followed by post-sampling analytical determinations in a geochemical laboratory, has been the favorite monitoring strategy, and still remains a key tool today, especially at dormant, closed-conduit volcanoes (Fischer and Chiodini 2015; Chiodini et al. 2016). Direct sampling, however, becomes increasingly impractical at open-vent volcanoes (Fig. 1a and c), where most of the gas output is sustained by widely-spaced emission of atmospheric plumes. At mafic open-vent volcanoes, temporal resolution of observations also matters, as transition from quiescence to eruptions can occur over much faster timescales (seconds to a few years at most) than the relatively slow reactivation intervals of dormant, more felsic volcanoes (typically occurring over timescales of months/years to even millennia; Costa et al. 2020). The last two decades have therefore entailed major efforts to develop increasingly sophisticated gas sensing units that can operate in near real-time to measure in-situ (in

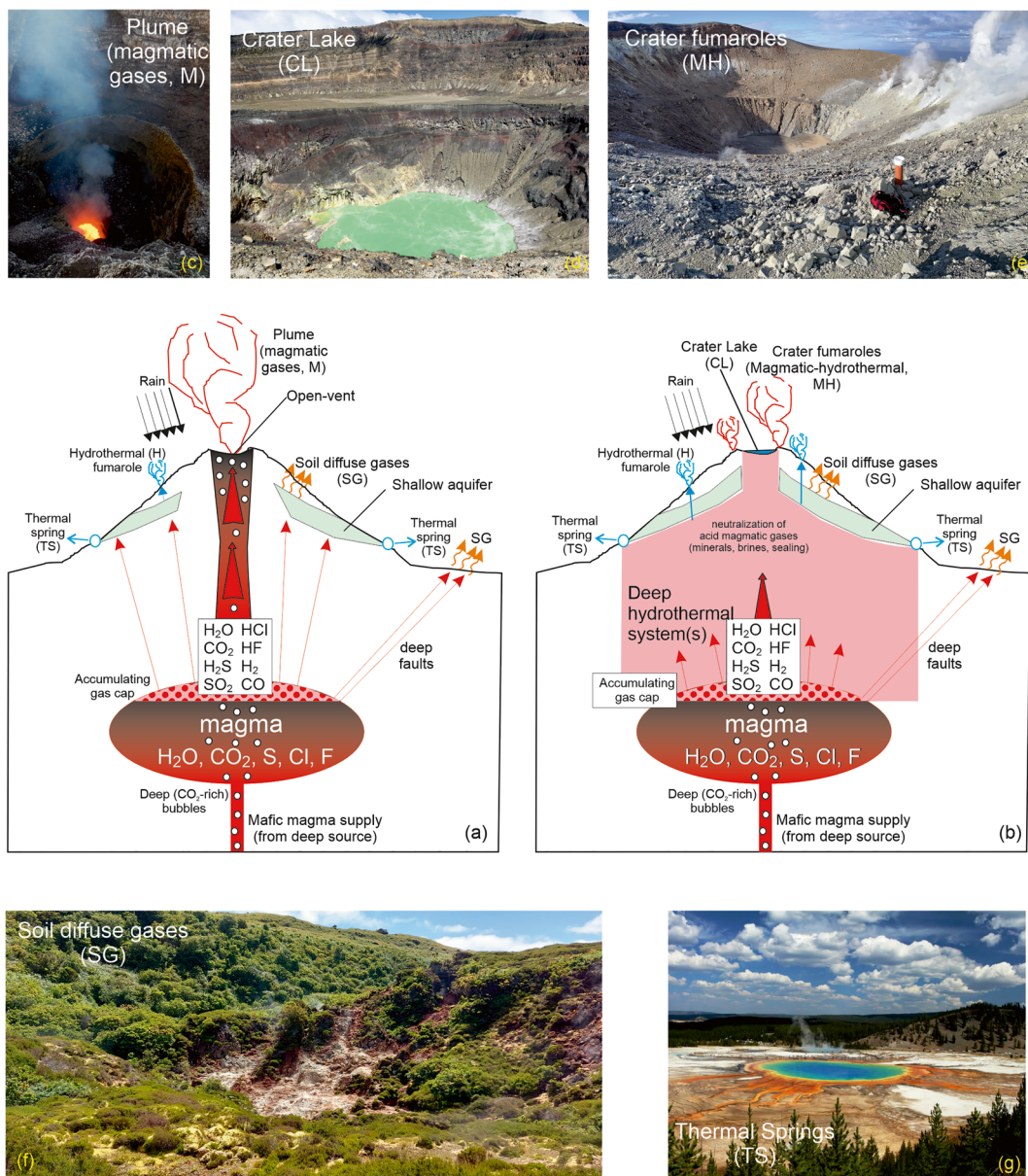


Fig. 1 Volcano cross-sections showing schematic plumbing systems for **a** open-vent and **b** closed-vent volcanoes. For both, the location of the various forms of volcanic fluid emissions, and the main source processes that govern their chemistries, are illustrated. Photos are examples of these different volcanic gas emission forms: **c** magmatic (M) gases delivered by open-vent plume degassing at Masaya volcano, Nicaragua (photo: A.A.); **d** an acidic, hot crater lake (CL), Santa Ana volcano, El

Salvador (photo: A.A.); **e** a closed-conduit, dormant volcano topped by a summit fumarole (F) field, typically discharging mixed (magmatic-hydrothermal, MH) fluids (La Fossa crater, Vulcano Island; photo modified from Aiuppa et al. 2022); **f** a diffuse degassing area discharging soil gases (SG) in the Furnas do Enxofre area, Terceira Island, Azores, Portugal (photo: F.V.); and **g** the grand prismatic thermal spring (TS) at Yellowstone volcano, USA (photo: S.I.)

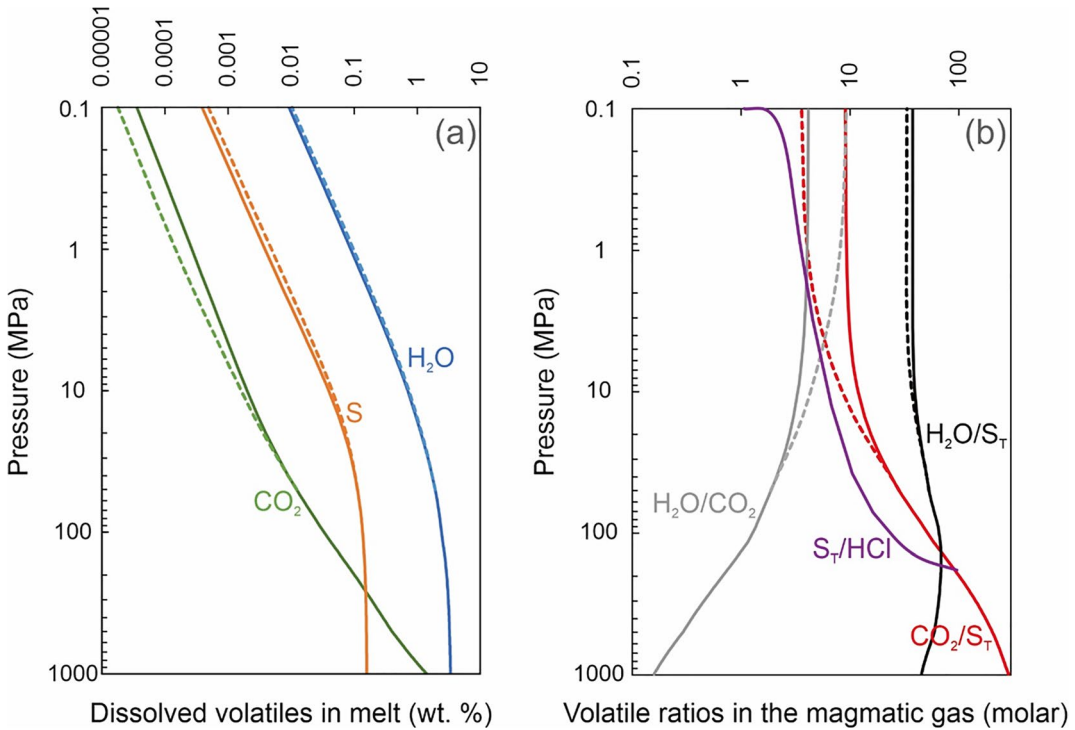


Fig. 2 Modelling volcanic degassing with a volatile-saturation code (Moretti et al. 2003; Moretti and Papale 2004). Panel **a** illustrates the model-calculated dissolved volatile contents in melt as a function of pressure (in MPa). The example illustrated is for a Stromboli volcano parental melt (same input conditions of Aiuppa et al. 2010a, b) stepwise decompressed from 1000 to 0.1 MPa in closed system conditions (solid lines). The dashed lines indicate the pressure-dependent evolution of dissolved volatiles in open-system degassing conditions (from 50 MPa to 0.1 MPa). Panel **b** shows the corresponding volatile (molar) ratios in the coexisting

equilibrium magmatic gas phase (S_T stands for total S and corresponds to $\text{SO}_2 + \text{H}_2\text{S}$). These model calculations demonstrate the sequential ($\text{CO}_2 > \text{H}_2\text{O} > \text{S} > \text{Cl}$) extraction of volatiles from an ascending mafic melt, and the pressure-dependent evolution of magmatic gas composition, from CO_2 -rich at high pressure to H_2O -S-rich at low pressure. The predicted pressure-dependent evolution of the magmatic gas S/HCl ratio at Stromboli is from Allard (2010), and based on empirical fit of melt inclusion data to derive bulk [(vapor + crystals)/melt] partition coefficients

the proximity of volcanic craters) the chemistry of volcanic plumes at high temporal resolution (seconds to minutes) (Aiuppa et al. 2005, 2007; Shinohara 2005). It has also become increasingly appreciated that, especially at closed-conduit volcanoes, diffuse emissions via degassing soils and aquifers can sustain a large fraction of the volatile output (Shinohara 2013; Taran and Kalacheva 2019; Werner et al. 2019), thus motivating instrumental measurement networks for soils/groundwaters as well.

The aim of this chapter is to review the basic concepts and more recent advances in volcano geochemical monitoring, with a special focus on in-situ methods of sampling/measurement. We discuss the methodological and scientific aspects of modern in-situ tools used to measure and interpret volcanic fluid *composition*, while remote gas-sensing tools that are central to also measuring the rates of volatile release (gas *flux*) are covered elsewhere (Campion et al., this book).

2 Monitoring Volcanic Fluids: Basic Principles

The goal of geochemical volcano monitoring is to identify changes in the composition of volcanic fluids (fumaroles, plumes, crater lake waters, soil gases, groundwater) that reflect changes in volcano activity state. With a rigorous time-series analysis (where sufficiently robust time-series exist), and assisted by quantitative modelling and interpretation, these chemical variations can contribute to forecasting eruption onset.

Volcanic fluid monitoring initially used an empirical approach. With time, when observations became more frequent and continuous, ‘precursory’ trends and patterns in the monitored geochemical parameters began to be identified prior to volcanic eruptions (e.g., Menyailov 1975). A major advance was realized when gas observations started to be tied to petrological information on volatile content and evolution in magmas (Gerlach and Graeber 1985; Allard et al. 1994), as made possible by the analysis of volatiles in silicate melt inclusions (Wallace et al. 2015, 2021) and fluid inclusions (Bodnar 2003; Hansteen and Klugel 2008). Another major breakthrough occurred in the late 1990s to early 2000s (Giggenbach 1996; Nuccio and Paonita 2001; Aiuppa et al. 2007; Edmonds 2008), when the first degassing models became available (Newman and Lowenstern 2002; Moretti et al. 2003), fueled by experimental and theoretical data on volatile solubility and vapor-melt partitioning (Carroll and Holloway 1994), and allowed quantitative modelling of the evolution of the magmatic gas phase in equilibrium with a silicate melt over the P-T-X evolution path experienced by magma during ascent and degassing (Fig. 2a and b).

Several processes (Fig. 3a) exist that can potentially alter the composition of volcanic fluids, ultimately causing the temporal changes captured by volcanic gas monitoring (Fig. 3b). It is the role of volcano geochemists, by analyzing data from the monitoring network at specific volcanoes, to resolve the respective roles played

by each of the potentially operative processes. As each of these implies distinct volcano behaviors and regimes, understanding the key controlling factor(s) holds profound implications for eruption likelihood.

At open-vent volcanoes worldwide (Carn et al. 2017; Aiuppa et al. 2019; Fischer et al. 2019; Werner et al. 2019) that are persistently erupting/degassing (Fig. 1a and c), magma is at the surface or shallow in the conduit (as revealed by visible and thermal imagery, e.g., Coppola et al. 2020), and is therefore the primary source of degassing. Under such conditions, the temporal fluctuations in magmatic degassing modes/regimes in the subsurface (Edmonds et al. 2022) primarily control temporal changes in gas composition (e.g., Aiuppa et al. 2007). Here, the key feature that volcano geochemists rely upon is the contrasting solubilities of individual gas species, which governs sequential extraction from melt to gas bubbles during magma ascent and decompression, from least soluble (e.g., CO₂, N₂, and noble gases) at high pressure to most soluble (e.g., S, halogens) at lower pressure (Giggenbach 1996; Edmonds 2008; Edmonds et al. 2022; Papale et al. 2022) (Fig. 2a). Volatile saturation codes (e.g., Moretti et al. 2003; Moretti and Papale 2004; Ding et al. 2023) that simulate isothermal (constant temperature) degassing of magmas predict how the equilibrium (with the melt) magmatic gas phase evolves during decompression, from CO₂-rich at high pressure, to H₂O-S rich at near-surface conditions (Figs. 2b and 3a). It is important to realize, however, that magmatic gases emitted at surface by open-vent degassing correspond to integrals of volatiles released by magma stored over a range of crustal depths (Christopher et al. 2015; Cashman et al. 2017; Edmonds et al. 2021); in such cases, iso- and polybaric second boiling processes (degassing due to crystallization) operate in conjunction with decompressional degassing to control gas chemistry. Isobaric degassing during prolonged crystallization of magma stored in crustal reservoirs can produce a segregated exsolved volatile phase whose temporal changes (caused by increasing

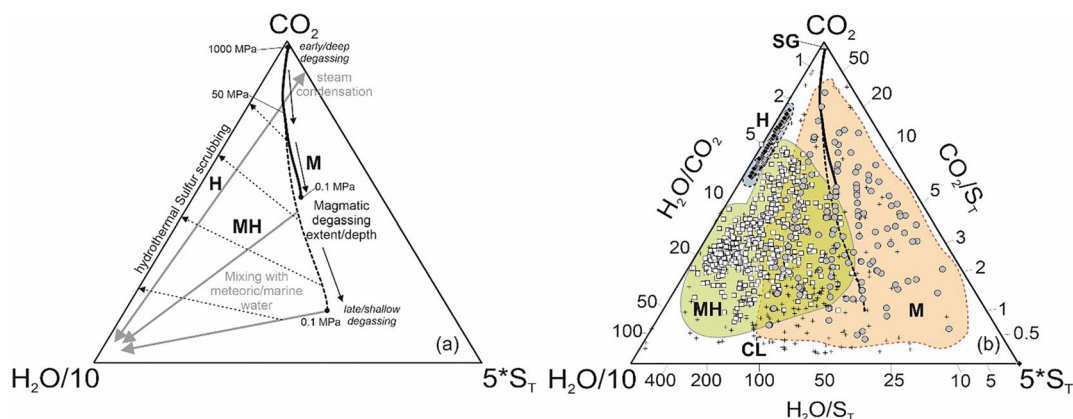


Fig. 3 **a** The key processes governing the composition of volcanic gases in a CO_2 – $\text{H}_2\text{O}/10$ – $5S_T$ space (S_T stands for total sulfur). Magmatic gases (M) released by open-vent (persistently active) volcanoes have composition controlled by extent/mode/depth of degassing of the source magma (and by its T–X conditions). They range from CO_2 -rich for deeply sourced magma (early vapors) to H_2O –S rich for late-stage, shallow magma degassing sources. This is expressed by the degassing lines (thick black line), drawn from the Stromboli degassing trends of Fig. 2. Magmatic-hydrothermal gases (MH) form in response to mixing of rising magmatic gases with hydrothermal steam formed by evaporating marine-meteoric fluids (see Fig. 1b). During hydrothermal processing, S scrubbing to hydrothermal solutions/minerals also occurs, leading to S-depleted hydrothermal (H) gases. Steam condensation in the subsurface leads to extremely CO_2 -rich compositions in soil gases (SG). **b** The

resulting compositional heterogeneity of volcanic gases and fluids. The S-rich magmatic gases are exemplified by the compositions of Stromboli plume (grey circles, data from Burton et al. 2007; Aiuppa et al. 2010a, b; La Spina et al. 2013; Pering et al. 2020). The HM field is illustrated by the composition of the more hydrous Vulcano Island fumaroles (open squares; data from Chiodini et al. 1993, 1995). The Campi Flegrei (Solfatara) fumaroles of Chiodini et al. (2017) (black diamonds) identify the S-poor hydrothermal (H) pole. Gases released by active crater lakes (CL, crosses; data from the global compilation of Hasselle 2019) span the entire compositional range, reflecting a complex interplay between magmatic degassing, mixing, steam condensation and S scrubbing. Soil gases are typically CO_2 -dominated as other gas species are removed by condensation and/or gas–water–rock interactions (Fig. 1b)

extents of crystallization) mimic those produced by magma degassing driven by ascent/decompression (Edmonds et al. 2021).

In light of the currently accepted paradigm that volcanic eruptions are most often triggered by overpressure development in deeply stored magma, driven by either resupply of gas-rich mafic magma or accumulation of bubbles due to second-boiling (crystallization-driven) of resident magma (Edmonds and Wallace 2017), model calculations suggest that volcanic eruptions should be preceded by a surge in CO_2 -rich gas emissions (Aiuppa et al. 2010a; Poland et al. 2012). Since H_2O (the most abundant volcanic gas species) is relatively difficult to measure in plumes (e.g., Shinohara et al. 2008; Aiuppa et al. 2010b; Girona et al. 2015), research has focused on measurement of the CO_2/S_T ratio (where

S_T is total S, typically corresponding to SO_2 in high-temperature magmatic gases; Aiuppa et al. 2017a, b). This is supported by model calculations (Fig. 3b) that indicate that high CO_2/S_T ratios are an ideal proxy for deep CO_2 degassing events, and therefore potentially unique indicators of impending eruption of mafic magma (Aiuppa et al. 2007, 2009a, b). Use of the volcanic gas CO_2/S_T ratio in volcano monitoring is more fully described in Sect. 3.1.2.

At closed-conduit volcanoes (Fig. 1b), the situation is complicated by typically deeper magma storage, so that any magma-sourced gas will have to pass through relatively thick piles of hydrothermally altered rocks, often pervaded by variably heated, infiltrated meteoric/marine fluids (Giggenbach 1987, 1996). This hydrothermal envelope, interposed between magma and

surface (Fig. 1b), is the locus of a multitude of chemical reactions (Chiodini and Marini 1998; Henley and Fischer 2021), and it is the extent to which these reactions take place (and their modalities) that mostly control surface fluid chemistry and its temporal variation (Stix and de Moor 2018). The tricky game for geochemists here is to shed light into magmatic processes through the veil left by hydrothermal reactions. These reactions act as both sources (e.g., they contribute re-evaporated meteoric/marine water to the gas stream; Taran and Zelenski 2015) and as sinks, especially by scrubbing water-soluble, reactive magmatic components such as SO_2 and HCl to hydrothermal solutions/minerals (Symonds et al. 2001; Fig. 3). Models/codes exist that can potentially help model magmatic gas scrubbing (Symonds et al. 2001; Marini and Gambardella 2005; Di Napoli et al. 2016); however, the extent to which these relatively simple models reproduce the naturally occurring reactions is unknown. For example, magmatic sulfur can be implicated in a variety of simultaneously occurring chemical reaction pathways, the roles of which vary as function of hydrothermal P-T-X conditions (Christenson et al. 2015; Stix and de Moor 2018; Henley and Fischer 2021), and which may not proceed at same rate. While models assume equilibrium, magmatic gas scrubbing may in fact be kinetically controlled. Irrespective of the reaction pathway that dominates (and whether or not the process is at equilibrium or kinetic), magmatic gas-hydrothermal reactions will sequester part of magmatic SO_2 (and HCl) into hydrothermal minerals/brines and convert part of SO_2 into H_2S (Henley and Fischer 2021). Hence, the fumaroles near the summit of closed-conduit volcanoes ultimately reflect mixing between hot, CO_2 - SO_2 -rich magmatic fluids and H_2S -rich, HCl -poor hydrothermal steam (Giggenbach 1987) (Fig. 3b). Careful scrutiny and modelling allow mixing proportions to be quantified (Paonita et al. 2013; Chiodini et al. 2016), and eventually capture the transition from hydrothermal-dominated to more magmatic compositions during volcano re-awakening (Vaselli et al. 2010). Nitrogen and light noble gases (He, Ar, Ne), owing to their

inert geochemical behavior, are especially useful tracers of mixing (Sano and Fischer 2013). Shallow (meteoric) and deep (magmatic) fluids also have contrasting H-O-C noble-gas isotopic signatures, making isotopes especially valuable mixing tracers (Oppenheimer et al. 2014). Closed-conduit volcanoes are thus the realm of fumarole direct sampling (see Sect. 3.1.1). The multi-species analytical determinations that only direct sampling allows also open the way to fully characterizing CO_2 - CO - CH_4 - H_2O - H_2 gas equilibria established during magmatic gas transit and re-equilibration inside hydrothermal systems (Chiodini and Marini 1998). Any temporal evolution of hydrothermal P-T conditions, as volcanoes become restless or during unrest, can therefore be reconstructed (Chiodini et al. 2016, 2021) (see Sect. 3.1.1).

Many closed-conduit volcanoes are topped by colorful, hot crater lakes (Fig. 1d). Their existence requires a closed crater and specific hydrologic regimes (appropriate climate and permeability; Taran et al. 2021), and their stability depends on the balance between water input and loss; they therefore have a limited temperature stability (Varekamp 2015). Should eruptions persist, lakes often quickly disappear, whether they are shallow lakes such as Poás (Rouwet et al. 2017) or much larger ones (Taal; Perttu et al. 2023). When crater lakes occur, they generally occupy a depression progressively filled with meteoric waters. Through time, volcanic fluids and rocks dissolve within these waters, providing a wide range of geochemical compositions and spanning a wide but bimodal (Marini et al. 2003) range of pH values.

Volatiles can also be emitted in a more sluggish, silent form through soils and aquifers from the surface of both open- and closed-systems volcanoes (Fig. 1). In such environments, only the least reactive magmatic volatiles (e.g., CO_2 , N_2 and noble gases) can freely move and degas. Fractures and faults are the preferential pathways for the percolation of gases from depth to the surface, establishing the close relation between diffuse emissions and tectonic structures which constitutes the basis for definition of “Diffuse Degassing Structures” (DDS) by

Chiodini et al. (2001). Diffuse emissions were first documented on the flanks of active volcanoes, such as Etna or Vulcano, where the CO_2 released was estimated to be of similar magnitude to the CO_2 emitted from fumaroles and crater plumes (Baubron et al. 1990; Allard et al. 1991). Over time, high CO_2 emissions have also been measured inside calderas of less active volcanoes, such as Mount Usu, Japan (Hernández et al. 2001), Campi Flegrei, Italy (Chiodini et al. 2003; Cardellini et al. 2017), Yellowstone, USA (Werner et al. 2000; Rahilly and Fischer 2021), Teide in the Canary islands (Hernández et al. 1998), and Furnas in the Azores (Viveiros et al. 2010). The soils near active volcanoes diffusively release CO_2 -dominated gas and, in some volcanic systems with active hydrothermal systems, diffuse degassing is even the primary mode of volcanic degassing, as for example at Campi Flegrei (Cardellini et al. 2017 and references therein). The diffuse soil CO_2 fluxes in different volcanic systems range from values below 100 t d^{-1} up to values higher than $10,000 \text{ t d}^{-1}$ (Werner et al. 2019 and references therein). The abundance of CO_2 in magmas, together with its low reactivity and solubility in silicate melts compared to other volatiles at similar pressure and temperature conditions (Gerlach and Graeber 1985), highlight the importance of including diffuse emissions in any volcano surveillance program. In addition, this type of degassing may contribute significantly to global volcanic CO_2 degassing, as discussed by Burton et al. (2013), Fischer et al. (2019) and Werner et al. (2019). Because CO_2 may also originate from soil respiration (microbial, plant and faunal activities) (e.g., Raich and Potter 1995), carbon isotopic composition ($\delta^{13}\text{C}$) is an important marker to discriminate the origin of the gases released (Hoefs 2004). Other deeply derived carbon sources include degassing of the terrestrial mantle and magma bodies and dissolution of carbonates over wide temperature ranges up to thermal metamorphism (Irwin and Barnes 1980; Nakamura et al. 1990).

CO_2 (plus N_2 , Ar and He) also dominates the dissolved gas phase in volcanic groundwaters and springs/hot pools. These waters

are extremely heterogeneous in composition. Although the bicarbonate ion (formed by acid dissolution of magmatic CO_2 in water) often dominates among the anions, dissolved chlorine and sulfate may become increasingly important where hotter magmatic condensates, or the outflow of hot, hydrothermal brines, contribute to aquifer recharge. Chemical changes in distal groundwater systems are often closely coupled with changes in groundwater pressure and temperature, thus in the section on groundwater modeling (3.5) we briefly consider physical changes as well. In operational practice, the feasibility of groundwater monitoring—both chemical and physical—depends on the availability of appropriately located springs and wells.

3 Methods, Applications, and Selected Case Studies: Geochemical Monitoring at Play

3.1 Monitoring Via Direct Sampling of Fumaroles

Direct sampling of fumaroles (Fig. 4) is the traditional method to gather information on the chemistry of the fluids emitted by volcanoes and hydrothermal systems. Contemporary sampling tools are the result of progressive implementation during the 1970s–1980s, led by numerous investigators (Giggenbach 1975; Cioni and Corazza 1981; Giggenbach and Goguel 1989).

3.1.1 Generalities on the Composition of Volcanic Fumaroles

Compositionally, two main types of fumaroles can be identified: (i) those from boiling hydrothermal systems (systems at temperatures below the critical temperature of water, containing a liquid phase; Fig. 3b) are mixtures of H_2O (80–99.9%), CO_2 (20–0.1%), H_2S (100–10000 ppm), plus a number of minor species (CH_4 , H_2 , CO , N_2 , Ar, He; see Chiodini and Marini 1998); and (ii) the fumaroles in high-temperature volcanic environments (Fig. 3b),



Fig. 4 Sampling of a fumarole with a Giggenbach flask (partially filled with NaOH) at Solfatara (Campi Flegrei, Italy). A sketch of the sampling line is shown in the inset

also dominated by H_2O and CO_2 , but characterized by the presence of acidic species (i.e., SO_2 , HCl , HF), and by much lower CH_4 contents, a gas species mainly formed in hydrothermal environments (see Giggenbach 1996). These compositional differences between the two environments are used for a first-order classification of fumaroles: hydrothermal and volcanic.

Fumarolic gases are typically collected by inserting a metal tube (generally titanium) housing a set of dewar pipes ('dewar' line in Fig. 4) into the fumarolic vent. This favors steam outflow while limiting condensation. Different sample types can be taken at the outlet of the 'dewar' line. Traditionally, the most common sample type is collected in an under-vacuum flask, 100–300 ml in volume, containing 30–100 ml of a 4 N NaOH solution ('Giggenbach flask', Fig. 4). The water vapor condenses and reactive gases (CO_2 , H_2S , SO_2 , HCl , HF) are dissolved in the solution, while non-condensable species (e.g. H_2 , CH_4 , CO , N_2 , Ar , He) are concentrated in the pre-evacuated headspace of the flask. Carbon dioxide, sulfur species and Cl and F absorbed in the alkaline solution are usually analyzed after oxidation (with H_2O_2) by acid–base titration (CO_2)

and by ion chromatography (S species, Cl, F). Non-condensable gases are determined by gas chromatography. Specific mass-spectrometers are used to determine isotope composition of gases (e.g. $^3\text{He}/^4\text{He}$, $^{15}\text{N}/^{14}\text{N}$, $^{40}\text{Ar}/^{36}\text{Ar}$, $\delta^{13}\text{C}$, δD , $\delta^{18}\text{O}$, $\delta^{34}\text{S}$; see Chiodini et al. 2012). The water content of the fumarole is computed as the difference between the total weight of the sample and the sum of the weight of the different determined species (see Giggenbach 1975; Giggenbach and Goguel 1989 for further details).

Non-condensable gases and condensates of water vapor can be sampled from the same 'dewar' line by flowing the fumarolic gases through a condenser (Cioni and Corazza 1981). The sample of non-condensable gases can be used for the gas-chromatographic determination of CO (a species that is not stable in the NaOH sample) and for isotopic analyses of the carbon and the oxygen of the CO_2 . The condensate of water is used for isotopic analysis of the water stable isotopes (^2H and ^{18}O) (Taran and Zelenski 2015).

3.1.2 Major Outcomes of Recent Research

Direct sampling contributes to modern volcano monitoring in a variety of substantial ways. Firstly, it provides invaluable information on the origin of fluids by permitting accurate multi-isotope determinations (3.1.3). Secondly, it opens the way to measurement of minor and trace elements that are key to using gas geothermometers and geobarometers (Chiodini and Marini 1998), and hence to investigation of T-P conditions of the gas source zone and its variations during volcanic unrest (3.1.4). Compositional changes of the fumaroles can also track magmatic gas injection into shallow hydrothermal systems during unrest (Chiodini 2009), ultimately providing geochemical data sets that can be compared with geophysical signals such as earthquakes and deformation (Chiodini et al. 2017).

In order to illustrate the potentialities of this technique, we describe two different examples: (i) use of direct sampling to infer the origin of

water discharged by volcanoes; and (ii) use of gas geothermometers to derive long-term (40 years) time-series of hydrothermal temperatures at Campi Flegrei, Italy.

3.1.3 Water Stable Isotopes of Volcanic-Hydrothermal Discharges

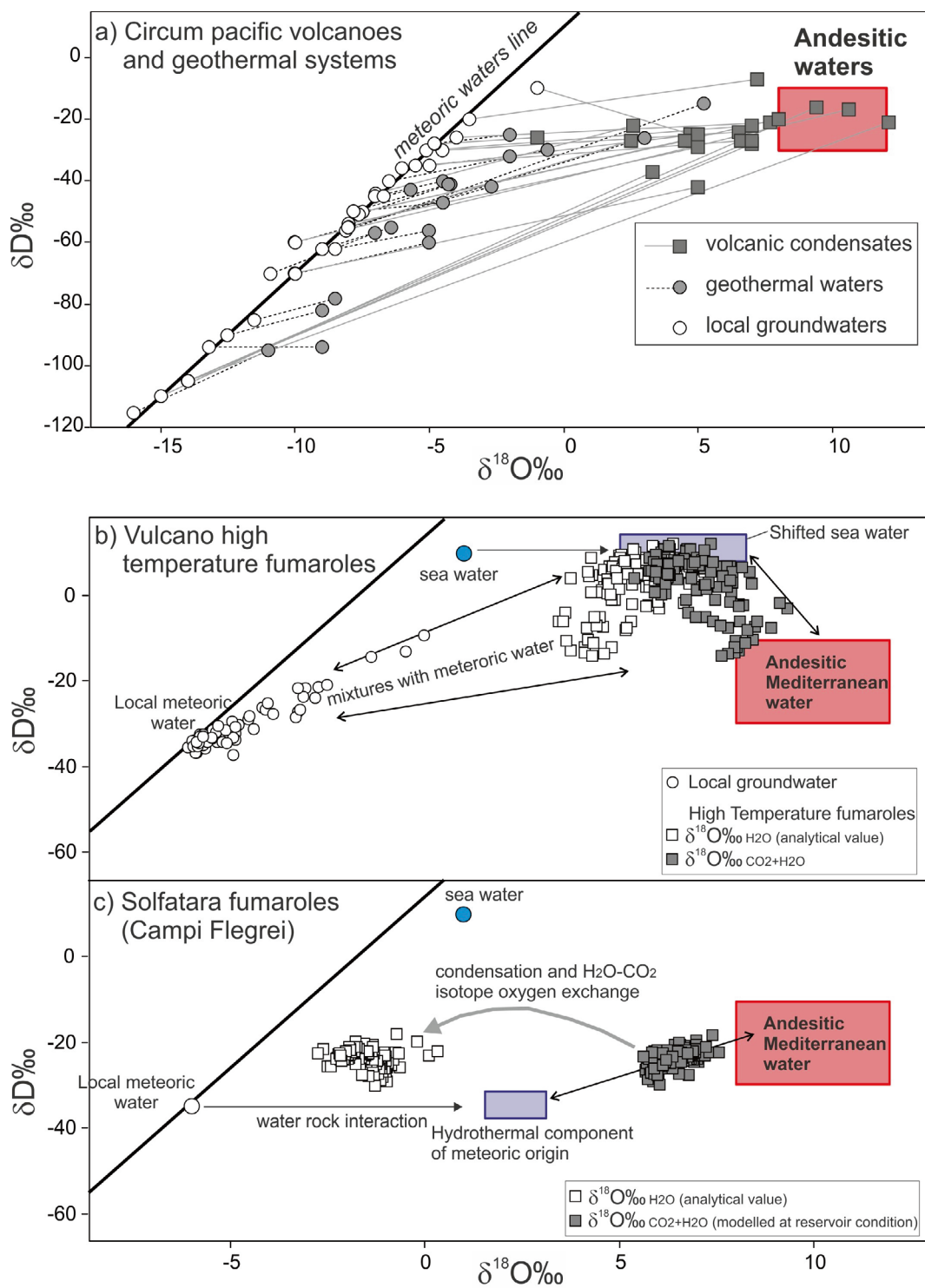
Taran et al. (1989) first used the term ‘andesitic water’ to describe the peculiar isotopic composition (δD and $\delta^{18}\text{O}$) of waters discharged by fumaroles on volcanoes of the Kamchatka peninsula. Subsequently, Giggenbach (1992a) reviewed the water-isotope signature of many geothermal waters and volcanic fumaroles of the circum Pacific region, discovering that all the considered systems discharge mixtures of local groundwater and a common magmatic endmember ($\delta\text{D} = -20\text{‰} \pm 10\text{‰}$; $\delta^{18}\text{O} = +10\text{‰} \pm 2\text{‰}$; Fig. 5a) that he named ‘andesitic water’, following Taran et al. (1989). Giggenbach (1992a) argued that subducted seawater could be the main source of this magmatic endmember. This seawater could be carried to the formation zone of arc magmas by fluids recycled from sediments, altered oceanic crust, and serpentinized mantle in the subducting slab.

More recently an ‘andesitic water’ type has also been inferred for some Mediterranean volcanoes (Vulcano island, Campi Flegrei, Nisyros; Chiodini et al. 2000; Chiodini et al. 2016; Dotzica et al. 2009). The cases of Vulcano and Campi Flegrei, where the fumaroles are particularly rich in CO_2 , are reported in Figs. 5b and c. In these specific cases, the analytical ^{18}O data are not directly interpretable, because the fluids are affected by a rapid isotope oxygen exchange reaction (between H_2O and CO_2) at the discharge temperature, a process that causes depletion in $\delta^{18}\text{O}$ of water (Chiodini et al. 2000). Once this correction is applied, a clear contribution of isotopically heavy andesitic Mediterranean water can be resolved in both examples, unambiguously proving the magma-degassing trigger for ongoing unrest at the two volcanoes (Fig. 5).

3.1.4 Use of CO/CO_2 Ratios to Infer Hydrothermal T-P Conditions

Gas geothermometers (Chiodini and Marini 1998) are based on the establishment of gas–gas or gas–mineral equilibria at hydrothermal P–T conditions. As magmatic gases fueling hydrothermal unrest are injected into hydrothermal systems, redox couples (e.g., CO/CO_2 , CH_4/CO_2) re-equilibrate at hydrothermal P–T conditions; these can hence be recorded in the composition of hydrothermal steam samples collected at the surface (provided no condensation—or further re-equilibration—has occurred during rapid steam ascent, expansion and cooling). Increasing hydrothermal P–T, when recorded, imply increased heat/fluid transport from the magmatic source, and hence is a sign of escalating unrest (Chiodini et al. 2016). A site where application of hydrothermal geothermometers has been especially insightful is the Solfatara crater of Campi Flegrei, Italy, whose fumaroles have a uniquely long and systematic compositional record dating back to the bradyseismic crisis of 1983–84. The database of fumarolic compositions, which now includes more than 650 fumarolic samples, has revealed important compositional variations in both major and minor components (see, e.g., Chiodini et al. 2016, 2021, 2022).

In order to illustrate the potential of the direct sampling method, we focus here on the temporal variations of carbon monoxide (CO), the fumarolic gas species most sensitive to temperature variations. The $\log(\text{CO}/\text{CO}_2)$ ratio (Fig. 6) can be used as a gas-geothermometer, considering the reaction $\text{CO}_2 = \text{CO} + 1/2\text{O}_2$ and a suitable buffer of the oxygen fugacity ($f\text{O}_2$). In the specific case of Campi Flegrei, the D’Amore and Panichi (1980) $f\text{O}_2$ –T empirical relation ($\log f\text{O}_2 = 8.20 - 23643/T_{(\text{K})}$) has been found to best approximate the redox conditions of the hydrothermal system (Chiodini et al. 2011). The resulting geothermometer, $T_{(\text{K})} = 3133.5 / (0.933 - \log(\text{CO}/\text{CO}_2))$, can then be used to investigate the temperature variation of the gas equilibration zone, which is assumed to be the top of the hydrothermal system feeding the Solfatara fumaroles (see Chiodini et al. 2021).



◀ **Fig. 5** Isotopic composition of volcanic condensates, geothermal waters, and local groundwaters from 20 volcanoes and 19 hydrothermal systems of the circum Pacific area (redrawn from Giggenbach 1992a, b). The considered systems are from the Americas, Indonesia, Japan, Kamchatka, New Zealand and the Philippines (see Giggenbach 1992a, b, for further details and pertinent references). Stable isotopes of the water discharged by the fumaroles of **b** Vulcano Island and **c** Solfatara

(Campi Flegrei, Italy). The analytical data are not directly interpretable, because oxygen isotopes of water are affected by re-equilibration with the oxygen of the CO_2 , a reaction occurring at the fumarolic discharge temperature (Chiodini et al. 2000). This bias was overcome by considering the total oxygen isotopic composition of H_2O and CO_2 for Vulcano (b, Chiodini et al. 2000) and the value recalculated at reservoir conditions for Solfatara (c, Chiodini et al. 2022)

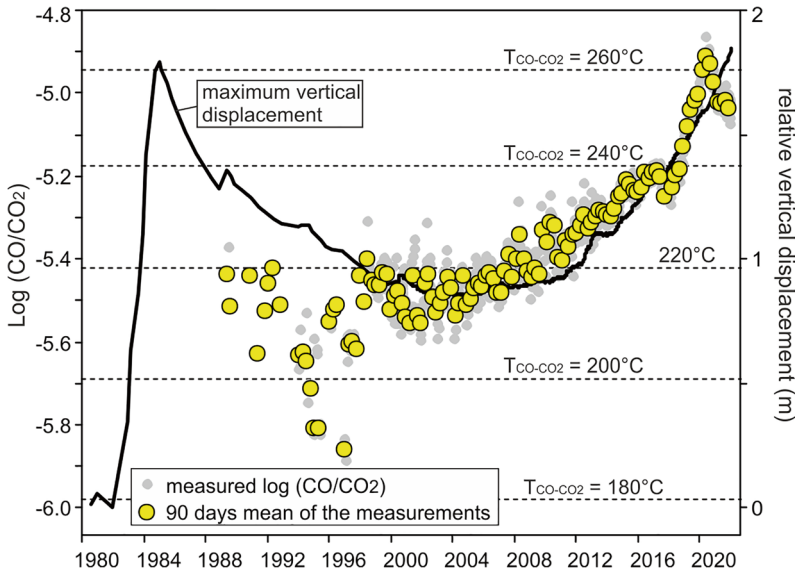


Fig. 6 Time variation of the fumarolic log (CO/CO_2) (circles) compared with maximum vertical deformation (line, Bevilacqua et al. 2022)

Figure 6 illustrates the $\log(\text{CO}/\text{CO}_2)$ variation observed in the two main Solfatara fumaroles. Before 2000, the CO/CO_2 -derived temperatures exhibited a wide scatter at 180–220 °C. From 2000 onward, progressive escalation is observed in the derived temperatures, from ~220 °C in 2000 to ~260 °C today, nicely paralleling ground uplift (Fig. 6). This observation is crucial for interpreting the ongoing volcanic unrest at Campi Flegrei, as it reveals a thermally driven process in which a progressive increase in hot magmatic fluid transport into the hydrothermal system is a key causal factor in the observed deformation (and seismicity).

3.1.5 Use of Noble Gases as Tracers of Mixing

Light noble gases (He and Ar) and nitrogen (N_2) have found large usage in volcanic gas science in view of their inert (or nearly inert for N_2) behavior that makes them useful indicators of the origin of fluids (e.g. Giggenbach and Poreda 1993). In volcano monitoring applications (Sano and Fischer 2013), noble gases are especially useful tracers to resolve mixing proportions between shallow atmospheric gases (that, at least in principle, prevail during volcano repose) and deeply generated (magmatic to mantle-derived) fluid components (that are expected

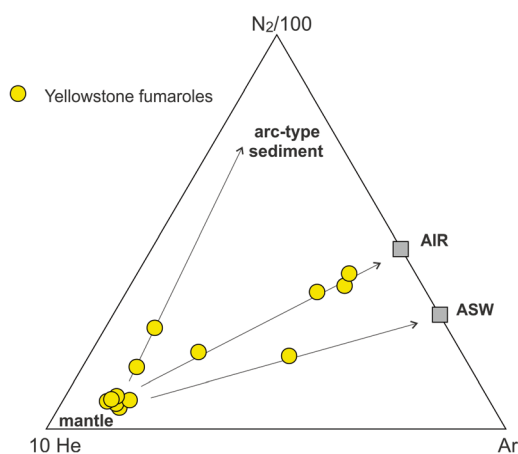


Fig. 7 N₂-He-Ar triangular plot for Yellowstone volcanic gases (re-drawn from Chiodini et al. 2012)

to increase as volcanoes become restless, e.g., Sano et al. 2015; Paonita et al. 2021).

As an example of the utility of N₂ and noble gases in volcanic gas science, we synthetically report here the case of Yellowstone fumaroles (Chiodini et al. 2012) for which He, Ar and N isotopes (³He/⁴He, ⁴⁰Ar/³⁶Ar, δ¹⁵N) are also available (Figs. 7 and 8).

A typical application is to compare the relative N₂-He-Ar proportions in a classical triangular diagram (Fig. 7; modified from Giggenbach and Poreda 1993; Giggenbach 1992b; 1996) to distinguish atmospheric vs. deep magmatic/mantle fluid components. In the Yellowstone case (Fig. 7), most of the samples plot exhibit He-rich compositions that are interpreted as representative of deep fluids, either sourced by mantle degassing (or deeply stored magma), or derived from a crustal fluid component enriched in ⁴He (produced by the decay of radioactive crustal elements such as U and Th). A few Yellowstone samples appear to have been contaminated by shallow fluid contributions, as they plot along mixing lines with air and air saturated waters (ASW) (Fig. 7). In contrast, N₂-enriched compositions are typically taken to resolve a fluid component derived by thermal processing of crustal sediments, and/or degassing of arc-type magmas; these latter contain a N₂-rich fluid component

derived from recycled sediments in the slab and incorporated in the source mantle wedge during slab volatilization (Fischer et al. 2002).

Further useful information on fluid source can be extracted from noble gas isotope systematics (Hilton et al. 2002; Sano and Fischer 2013; Oppenheimer et al. 2014; Fischer and Chiodini 2015). This is because atmospheric, crustal and mantle-derived fluids have contrasting noble gas isotope signatures as do the various mantle domains (depleted, primitive, enriched) that are characterized by distinct isotope compositions (Sano and Fischer 2013). As an example, we illustrate in Fig. 8 the ⁴⁰Ar/³⁶Ar ratios of Yellowstone gases plotted against their (a) ⁴He/⁴⁰Ar and (b) ³He/⁴He compositions. In the figures, the Yellowstone fumaroles are compared with the typical compositions of mantle plumes (that are high in primordial ³He), of the upper (depleted) mantle (that is richer in radiogenic ⁴He relative to “plume” He) and with atmospheric endmembers (air/ASW; both characterized by low-³He, low-⁴⁰Ar compositions). The composition inferred by Chiodini et al. (2012) for the Yellowstone deep magmatic component (MC in Fig. 8) has ³He/⁴He ratio composition of ~22 R/Ra (where Ra is the ³He/⁴He atmospheric ratio 1.384 × 10^{−6}) and ⁴He/⁴⁰Ar ~1, corroborating that fluids originate primarily from a mantle plume source rather than from the depleted upper mantle. The diagrams also show that the Yellowstone fumaroles peculiarly depart from those predicted from simple mixing between atmospheric and deep (MC) gases, suggesting the presence of an additional crustal component rich in radiogenic ⁴He and ⁴⁰Ar. The contemporary presence of atmospheric, crustal and deep mantle components, mixing in different proportions, explains the wide range of He isotope compositions (from 2 to 16.5 R/Ra in the 2007 samples studied by Chiodini et al. 2012) observed in Yellowstone fumaroles (see also Kennedy et al. 1985). Broadly speaking, the Yellowstone example clearly demonstrates the utility of noble gases as tracers of fluid origin.

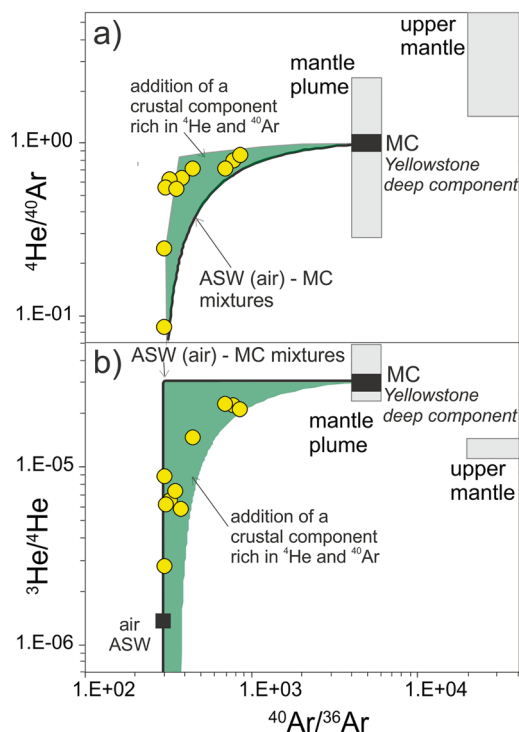


Fig. 8 He and Ar isotope composition of Yellowstone volcano gases (re-drawn from Chiodini et al. 2012). Data reflect mixing between atmospheric fluids (air, and air-saturated waters, ASW) and deep magmatic component (MC). The green shaded area exemplifies the addition of a crustal component (groundwater) enriched in radiogenic He and Ar. The gray box of relevant end-members (i.e. mantle plume and upper mantle) were drawn using: the $^{40}\text{Ar}/^{36}\text{Ar}$ ratios reported in Marty and Dauphas (2003) and the $^4\text{He}/^{40}\text{Ar}$ and $^3\text{He}/^4\text{He}$ in Trieloff et al. (2000) for the mantle plume; the $^{40}\text{Ar}/^{36}\text{Ar}$ and $^4\text{He}/^{40}\text{Ar}$ ratios of Moreira et al. (1998) and $^3\text{He}/^4\text{He}$ ratios of Marty and Zimmermann (1999) for the upper mantle

3.2 In-Situ Volcanic Plume Monitoring

3.2.1 The Concentration Ranges of Volcanogenic Gas Species in Plumes

Volcanic plumes form as the result of dispersion and dilution of volcanic gases in the background (ambient) atmosphere. As such, the typical gas concentration levels in plumes depend on source strength (initial concentration of gas species in the undiluted volcanic gas phase, and gas flux) and on the extent of dilution (which depends

on distance from source and atmospheric conditions, e.g., plume speed and direction, turbulence, etc.). This is schematically illustrated in Fig. 9, in which we model the atmospheric dilution of a pure magmatic gas phase (molecular composition calculated at equilibrium at 1100 °C and 1 bar using the HSC thermochemical code; <https://www.hsc-chemistry.com/>) in pure air. The characteristic near-vent (tens to hundreds of meters from source) and distal (km from source) plume environments are indicated, as identified based on typically measured SO_2 concentrations (e.g., Aiuppa et al. 2006, 2007; Delmelle et al. 2002; Whitty et al. 2020).

The diagram highlights that in-situ observations are typically taken in extremely diluted magmatic gas-air mixtures (magmatic gas/air mixing fractions of <0.1 ; Fig. 9): this is because, for safety reasons and/or owing to vent geometry constraints, denser plumes are normally not accessible, so that the plumes have aged seconds to minutes (being diluted by air) before they can be intercepted by any sensing device. In such conditions, only a relatively minor number of volcanogenic gas species (H_2O , CO_2 , SO_2 , H_2 , HCl , CO , H_2S , HF , and perhaps HBr ; see Fig. 9) are expected at measurable levels (e.g., at ≥ 1 ppmv). The diagram also shows that H_2O and CO_2 are the most abundant volcanogenic gas species in plumes, with predicted concentration levels of thousands of ppmv (Fig. 9). However, it is often difficult to resolve these volcanogenic levels above the ambient air background that already contains these gases in large amounts (thousands of ppmv for H_2O and 420 ppmv for CO_2). The gas species having the largest plume/ambient air contrast are SO_2 , H_2S , and the halogenic acids (HCl and HF), which are typically present in ambient air at (sub)ppb levels (Fig. 9).

3.2.2 SO_2 /Halogen Ratios

Given the results illustrated in Fig. 9, it is not surprising that SO_2 , HCl and HF are the species first targeted for monitoring by volcano geochemists. In addition to remote sensing techniques such as Fourier Transform InfraRed spectroscopy (FTIR; Francis et al. 1998; covered in

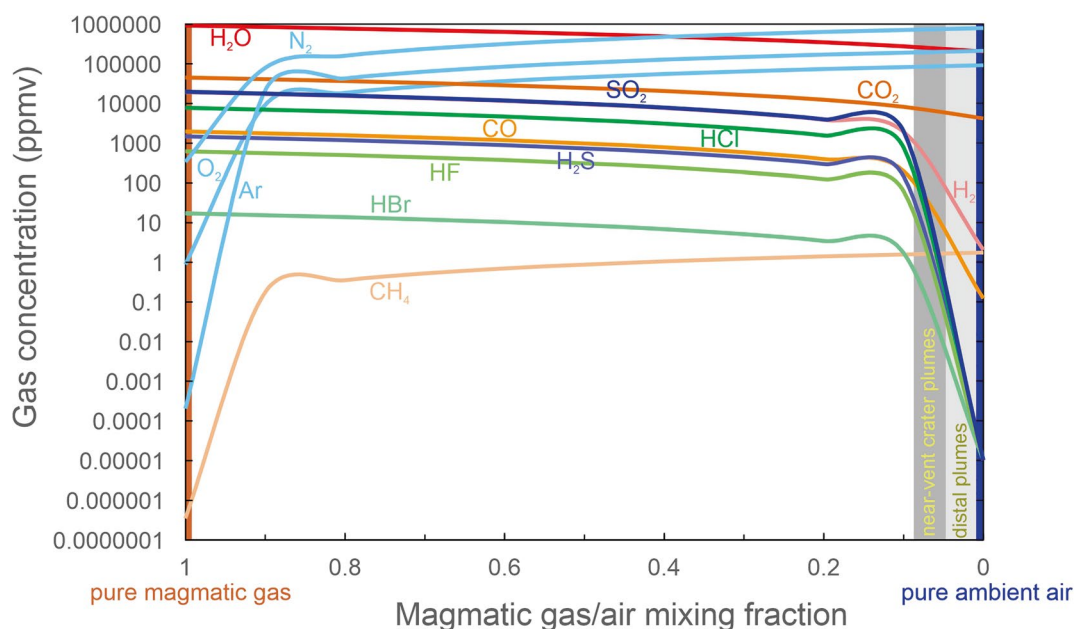


Fig. 9 Gas concentration ranges in near-vent (tens to hundreds of meters from source) crater plumes (dark gray shaded area) and distal (km from source) plumes (light gray shaded area). The plot shows expected gas concentrations obtained by increasing extents of dilution (from left to right) of a pure magmatic gas (narrow dark brown shaded area; magmatic gas/air mixing fraction=1) with pure air (narrow blue shaded area; magmatic gas/air mixing fraction=0). The pure magmatic

gas composition is obtained by calculating (with the HSC thermochemical software) the hypothetical equilibrium molecular composition of typical arc gas (Gerlach, 2004) at 1100 °C temperature and 1 bar pressure (redox at two log units above the FMQ buffer). For ambient air, we assume molar fractions of 0.2 (20,000 ppmv) for H_2O and 10^{-11} for sulphur species and halogens (air concentrations of all other gases are from Seinfeld and Pandis 2006)

this book in Campion et al.), a variety of in-situ methods have been employed for sampling of plume SO_2 , HCl and HF , exploiting the fact that these reactive acidic species have strong affinity for (can be trapped and accumulated in) adsorbing alkaline media. In-situ sampling was initially realized by actively forcing (with a pump) the plume to bubble through alkaline solutions (Williams et al. 1990) and/or filters impregnated with alkaline solutions (filter packs; Finnegan et al. 1989; Aiuppa et al. 2002), and more recently by using diffusive tubes (Aiuppa et al. 2004), bubblers (de Moor et al. 2013), alkaline traps (Wittmer et al. 2014), and denuders (Rüdiger et al. 2021).

All of the methods above, including FTIR, aim to characterize the volcanic gas plume SO_2/HCl and SO_2/HF ratios. Use of these ratios for volcano monitoring purposes is motivated by the distinct

gas/melt partitioning behavior of these gas species (Zajacz et al. 2012; Webster et al. 2018). Silicate melts are never saturated in a pure sulfur or pure halogen vapor/fluid phase; therefore, the degassing behavior of these species is governed by the partitioning behavior between a silicate melt and a $\text{H}_2\text{O}-\text{CO}_2$ magmatic vapor phase (e.g., by the vapor/melt partition coefficient, being the ratio of S/Cl/F concentrations in the coexisting vapor and melt; see review by Edmonds and Wallace 2017). Such vapor/melt partition coefficients have been determined for a variety of melt compositions and over a range of temperature, pressure and redox conditions (Baker and Alletti 2012; Zajacz et al. 2012; Webster et al. 2018; Ding et al. 2023). Once integrated in $\text{H}_2\text{O}-\text{CO}_2$ solubility models (Ghiorso and Gualda 2015), these vapor/melt partition coefficients allow prediction of SO_2/HCl and SO_2/HF ratios in the gas

phase released by magmas along their decompression path (e.g., Alletti et al. 2014; Burgisser et al. 2015). Problems remain, however, as our understanding of vapor/melt partitioning is far from complete, or even adequate, for the majority of magma P-T-X conditions, especially for halogens. Therefore, simpler approaches have also been used that empirically constrain S and halogen degassing behavior from analysis of volcanic gases (Edmonds et al. 2009; Aiuppa 2009; Cadeaux et al. 2018) or melt inclusions (Spilliaert et al. 2006; Allard 2010). In spite of these complexities, consensus has been reached that S is a more volatile species (higher vapor/melt partition coefficient) than halogens, especially in oxidized silicic (Scaillet et al. 1998) and mafic (Ding et al. 2023) melts. This causes a large fraction of the originally melt-dissolved S to be degassed to the gas phase starting from 100–150 MPa pressure (Spilliaert et al. 2006), or even deeper (>200 MPa; Ding et al. 2023). In contrast, calculations and observations suggest that only a minor fraction of the dissolved halogen cargo is partitioned to the gas phase, and generally only when magma confining pressure is low (<10 MPa; Edmonds et al. 2009); that is, at near-eruption conditions.

In such an interpretative framework, high SO_2/HCl and SO_2/HF ratios in surface volcanic gases are expected to mark the separate ascent of deeply originated gas bubbles (Allard et al. 2005; Burton et al. 2007), sourced by ascending (and degassing during de-compression) volatile-rich magma. In contrast, low SO_2/HCl , SO_2/HF and HCl/HF ratios should reflect late-stage magma degassing phases, such as during the terminal stages of basaltic eruptions (Aiuppa et al. 2002, 2009a, 2009b; Aiuppa 2009), or during quiescent degassing in “calm” volcanic activity phases (when shallow, volatile-depleted conduit magma is the major source of volatiles; La Spina et al. 2010) (Fig. 10).

The utility of SO_2/HCl and SO_2/HF ratios in volcano monitoring is illustrated by the Stromboli 2003 example in Fig. 10a (modified from Aiuppa and Federico 2004). The authors examined—using diffusion tubes—the

temporal evolution of SO_2/HCl and SO_2/HF molar ratios in the Stromboli plume from March to September 2003, a period encompassing a powerful paroxysmal explosion on 5 April. They observed unusually high SO_2/HCl (>4) and SO_2/HF (>10) compositions in the plume in the days prior to the paroxysmal explosion, well above those typical of background compositions observed during quiescent, ordinary activity (SO_2/HCl of ~1: Burton et al. 2007). Guided by models that predict the evolution of SO_2/HCl ratios in the magmatic gas phase released, upon increasing extents of degassing, from decompressing Stromboli melts (Figs. 2b and 8b; Burton et al. 2007; Allard 2009; Aiuppa 2009), Aiuppa and Federico (2004) interpreted the pre-paroxysm SO_2 -rich compositions as reflecting the precursory quiescent emission of a deeply sourced gas, released by the soon-to-erupt, decompressing mafic magma that later fed the explosion. In contrast, the transition toward increasingly SO_2 -poor and $\text{HCl}+\text{HF}$ -rich compositions in the months following the paroxysm (Fig. 10a) was interpreted as progressive recovery towards background level activity, in which the shallow resident conduit magma (filled with S-depleted, residual magmas) sustains the plume (Fig. 10b) (Aiuppa and Federico 2004).

As with fumarole direct sampling (3.1.1), the in-situ plume sampling techniques discussed above suffer from poor temporal resolution and lack of real-time data availability; the hazardous field operations and time-consuming post-sampling laboratory work limit the temporal resolution of observations to one per week/month in the most favorable cases (Aiuppa et al. 2002, 2004). While new sensors for real-time HCl analysis in plumes have recently been successfully tested (e.g., Roberts et al. 2017), their durability and stability for long-term gas monitoring with permanent devices remain unproven. Likewise, the operation of in-situ operating FTIR spectrometers in the proximity of active craters has revealed technical challenges (La Spina et al. 2013). Therefore, geochemists still must rely to large extent on discontinuous HCl (and HF) volcanic gas time-series.

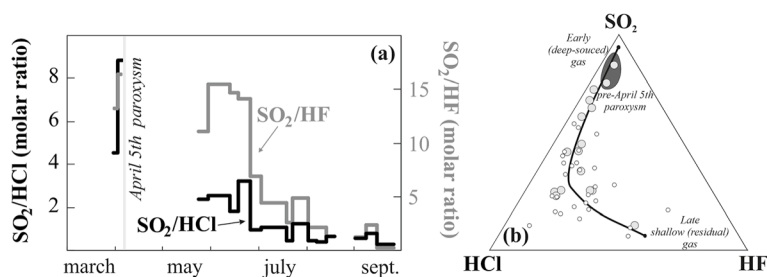


Fig. 10 **a** Temporal evolution of SO_2/HCl and SO_2/HF molar ratios in the Stromboli plume from March to September 2003, as inferred from in-situ plume monitoring using diffusive tubes (modified from Aiuppa and Federico 2004). High SO_2 compositions ($\text{SO}_2/\text{HCl} > 4$ and $\text{SO}_2/\text{HF} > 10$) are observed in the days prior to a paroxysmal explosion on April 5th, indicating precursory emission of a deeply sourced (Burton et al. 2007) gas prior to the blast; **b** SO_2 - HCl - HF relative proportions in the Stromboli 2003 gas plume (same data as in (a)) are shown by large grey symbols, and demonstrate the evolution from SO_2 -rich (pre-April 5th paroxysms phase) to increasingly SO_2 -poor and HCl - HF -rich after

the explosions (May to September 2003). For comparison, the 2004–2005 Stromboli gas plume compositions, indicative of background (regular Strombolian) activity are also shown (small open circles). The solid black line is the predicted model evolution (from Aiuppa 2009) of a gas phase released in open-system (Rayleigh-type) degassing from conditions of a Stromboli melt. Early vapors (early deep-sourced gas) are predicted to be SO_2 -rich, and the model gas is predicted to become halogen-rich in late (shallow) residual degassing stages. The model uses S and halogen partition coefficients adapted to fit the gas plume data (see Aiuppa 2009, for details)

An additional important limitation of in-situ plume sampling techniques is that they provide no information on the two most abundant volcanic gas species, H_2O and CO_2 . Thus, in the early 2000s, the volcanic gas community was in urgent need of a novel gas sensing technique that could allow real-time analysis of all major volcanic gas species in plumes, including H_2O and CO_2 ; this is when and why the Multi-GAS came into play.

3.2.3 The Multi-GAS and the CO_2/SO_2 Ratio Indicator

The Multi-component Gas Analyzer System (Multi-GAS) was simultaneously developed by two independent teams in Japan (Shinohara 2005) and Italy (Aiuppa et al. 2005). The two teams rapidly joined to advance implementation, refinement, and standardization of the technique (Aiuppa et al. 2006, 2007; Shinohara et al. 2008).

The idea that guided development of the Multi-GAS system was to design a compact, robust, and easy-to-use multi-sensor device for real-time detection of major gases in volcanic plumes. The basic principle is relatively

simple: a set of ad hoc-calibrated, miniaturized sensors—typically a near-dispersive infra-red spectrometer (for CO_2 and H_2O), and 1 to 3 gas-specific electrochemical sensors (for SO_2 , H_2S and H_2)—are assembled in series, and housed in a rugged box (Fig. 11a and b). The target gas (the volcanic plume) is pumped through the sensors, and the output signals are captured (at 0.5–1 Hz rate) and stored by an onboard data logger, where they are converted into gas concentration time-series using in-house calibration functions (Fig. 11c). These are then post-processed to calculate gas/gas (e.g., CO_2/SO_2 ; Fig. 11d) ratios in the plume.

At the time that it was conceived, the Multi-GAS teams exploited the maturation (and diffusion in the market) of increasingly stable electrochemical sensors, originally developed for detection of toxic gases in environmental studies for industrial settings. What insured success of the technique was its relatively low cost (<20 k€), simple operability and, especially, its robustness in surviving long-term exposure in harsh, aggressive volcano environments.

The Multi-GAS has been used in three main operational modalities. Initial applications used

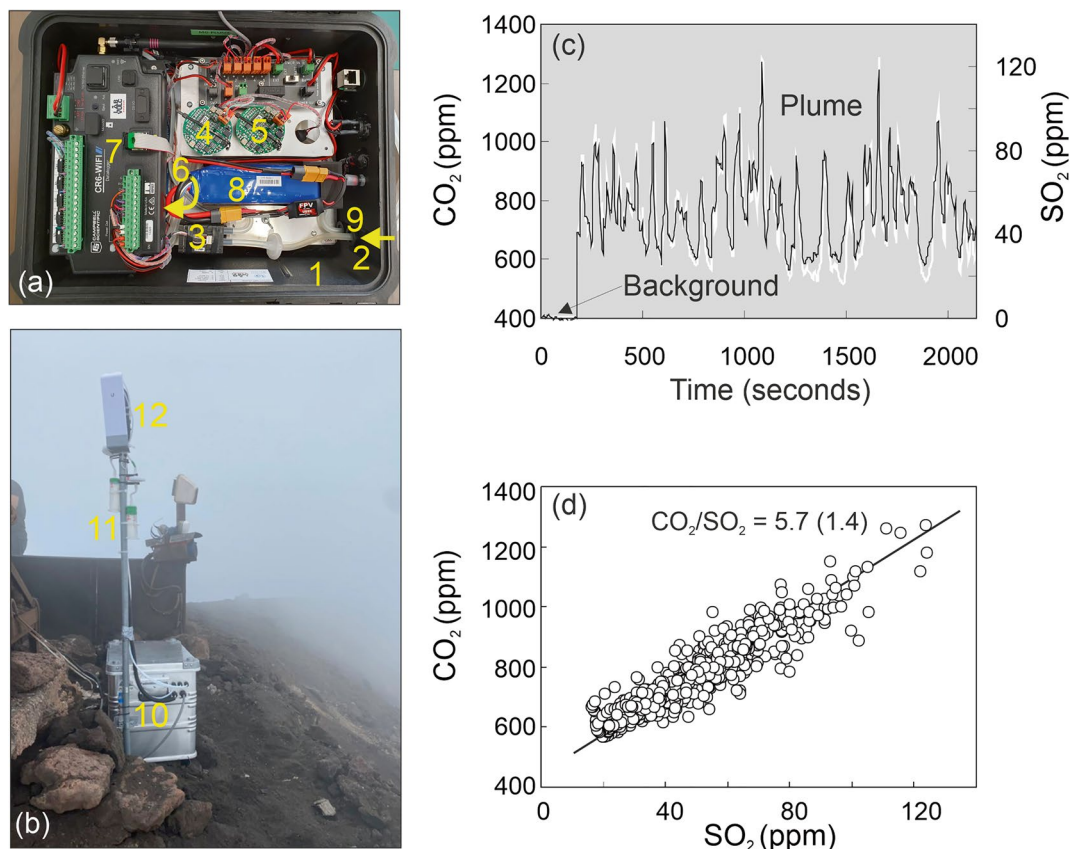


Fig. 11 Photo of multi-GAS unit and examples of multi-GAS concentration time-series. **a** Inside view of a Multi-GAS unit. Sensors are assembled in a water-proof case (1). Gas from the external gas inlet is pumped (2) by a miniaturized pump (3) through 2 electrochemical sensors (4–5) and one infra-red spectrometer (6), connected in series. Sensor output is captured by a commercial datalogger (7). A portable unit (as illustrated) is powered by an internal battery (8). The exhaust gas exits the Multi-GAS from the output tubing line (9). **b** Field deployment of a permanent, fully automated Multi-GAS for long-term gas monitoring. The whole unit (shown in **a**) is housed in an aluminum case (10) also containing

a set of large car batteries. The inlet system (11) captures the gas plume. A radio antenna (12) is used for data transfer to base station. **c** Example of a Multi-GAS derived concentration time-series (black; CO₂; white, SO₂), captured at 1 Hz in the Mt. Etna plume (modified from Aiuppa et al. 2006). CO₂ and SO₂ concentrations in the plume greatly exceed the background atmospheric levels (420 ppmv and <0.1 ppmv, respectively). **d** Same data as (c) plotted in a SO₂ versus CO₂ concentration scatter plot. The (molar) average CO₂/SO₂ ratio (5.7 in the example) in the selected temporal window is derived from the slope of the best-fit regression line (error, 1.4, as given by 1 standard deviation)

light, compact, portable versions for campaign-style plume measurements (Aiuppa et al. 2005, 2006, 2007; Shinohara 2005; Shinohara et al. 2008). A large fraction of the Earth's most actively degassing volcanoes (Carn et al. 2017) have now been covered by such campaign-style Multi-GAS surveys (Aiuppa 2015; Aiuppa et al. 2017a, 2019). A major step ahead was the first prototyping of instruments (at Stromboli and

Etna volcanoes in Italy; Aiuppa et al. 2009a, 2009b, 2010a, 2010c) that could be permanently deployed in crater environments to achieve long-term, fully automated gas observations, with data telemetered to a base station (the local volcano observatory; Fig. 11b). These permanent Multi-GAS instruments have now been deployed at many volcanoes worldwide, including in Japan (Shinohara 2015, 2017,

2018, 2020), USA (Kelly et al. 2015), Central America (Aiuppa et al. 2014, 2018; de Moor et al. 2016a, 2016b, 2019; Battaglia et al. 2019), South America (Aiuppa et al. 2017b; Lages et al. 2019), Iceland (Ilyinskaya et al. 2015), Indonesia (Syahbana et al. 2019) and elsewhere in the context of the Deep Carbon Observatory research initiative (Fischer 2013; Fischer et al. 2019; Werner et al. 2019). More recently, another breakthrough has arisen from the advent of even lighter and more compact units (Stix et al. 2018; Liu et al. 2019, 2020) that can be transported in Unmanned Aerial Systems (UAS) (James et al. 2020). Airborne, UAS-based measurement has expanded the field of operation of the Multi-GAS to remote, poorly accessible volcanoes (e.g., Liu et al. 2020) and/or erupting volcanoes (de Moor et al. 2019; Syahbana et al. 2019; Halldórsson et al. 2022).

When near-vent environments are accessible for Multi-GAS observations of dense plumes (Fig. 9), a broad spectrum of plume gas species (H_2O , CO_2 , SO_2 , H_2S , H_2) can be characterized (HCl is detected more rarely: Roberts et al. 2012, 2017). In such fortunate cases, the Multi-GAS allows quantification of the total volatile budget of a volcano (Aiuppa et al. 2008; Padrón et al. 2012), permitting comparison of gas compositions with degassing models (e.g., Fig. 3b) and thereby constraining the modes/regimes of degassing (Aiuppa et al. 2007, 2010a, 2017a, b, 2018), the source depth of the emitted gases (Aiuppa et al. 2007; Edmonds 2008), the magmatic vs. hydrothermal contributions (Shinohara et al., 2011; de Moor et al. 2016a, 2019; Stix and de Moor 2018), and ultimately the source magma redox and temperature (Moussallam et al. 2019, 2022). However, long-term observations are difficult for many of these gases (especially H_2O and H_2), so that most Multi-GAS applications have concentrated on the more easily detectable CO_2/SO_2 and $\text{H}_2\text{S}/\text{SO}_2$ ratios, and on the CO_2/S_T ratio in general (where $S_T = \text{SO}_2 + \text{H}_2\text{S}$).

The volcanic gas CO_2/S_T ratio has been monitored with increasing success in both volcano contexts discussed above (Fig. 1). At active, open-vent volcanoes (Fig. 1a and c), use of the

volcanic gas CO_2/S_T ratio is motivated by the large solubility contrast of carbon and sulfur in silicate melts. As model calculations show (Figs. 2 and 3), CO_2 is less soluble than S, and will therefore be early exsolved from mafic magma during migration from the mantle source to the lower/upper crust. Calculations (Figs. 2 and 3) and observations in fluid (Frezzotti and Touret 2014) and melt (Wallace et al. 2015, 2021) inclusions strongly corroborate the idea that CO_2 dominates the gas phase coexisting with the melt at mantle to deep/mid-crust conditions. If the deeply originated, CO_2 -rich gas bubbles are buoyant enough to ascend separately from mafic magma at depth, perhaps as magma stalls or is temporarily stored at some structural or rheological discontinuity in the crust (Menand and Phillips 2007; Christopher et al. 2015; Caricchi et al. 2018; Edmonds 2021; Edmonds et al. 2022; Rasmussen et al. 2022), then a high CO_2/S_T ratio gas signal can be recorded in the chemistry of surface gas emissions weeks to even months prior to final magma ascent and eruption (Aiuppa et al. 2021). Notably, this precursory increase in the CO_2/S_T ratio gas should, at least in principle, be easily resolvable by instrumental (Multi-GAS) monitoring; this is because model calculations (Figs. 2b and 3c) and observations (Aiuppa et al. 2017a) predict that, during ‘calm’ activity periods, volcanic gases will exhibit relatively lower (and constant) CO_2/S_T ratio signatures, consistent with degassing sustained by shallow resident conduit magma (the CO_2/S_T ratio is predicted to be especially low for open-system, late degassing of shallow magmas; see Figs. 2 and 3).

These model expectations first found experimental confirmation on the occasion of Etna’s 2006 (Aiuppa et al. 2007) and Stromboli’s 2007 (Aiuppa et al. 2009a, b, 2010a) eruptions, when eruption of mafic magma at the surface was preceded (by weeks) by the quiescent release of unusually CO_2 -rich gas (e.g., by increasing CO_2/S_T ratios and CO_2 fluxes in the plume). Precursory CO_2/S_T variations have since been found at many other volcanoes worldwide and in a variety of contexts (see review in Werner et al. 2019), including before basaltic explosive

eruptions (de Moor et al. 2016a; Aiuppa et al. 2017a, b), effusive eruptions (Poland et al. 2012), and lava lake formation (Aiuppa et al. 2018). Multi-GAS-based instrumental observations of the plume $\text{CO}_2/\text{S}_\text{T}$ ratio are now routinely performed by an increasing number of volcano observatories, and increasingly sophisticated measurement and data-processing techniques are being developed to resolve even subtle gas variations prior to short-lived, discrete explosions.

An example of state-of-the-art volcanic gas $\text{CO}_2/\text{S}_\text{T}$ time-series analysis is illustrated by the Stromboli case study of Fig. 12. The figure summarizes the results of one year (2020) of Multi-GAS observations of the plume CO_2/SO_2 ratio ($\text{S}_\text{T} \approx \text{SO}_2$ in magmatic gases) during a phase of regular Strombolian activity, interrupted by four larger-than-normal ('major'), short-lived explosions ($\text{VEI}=1$) (indicated by stars). Traditional post-processing techniques (Aiuppa et al. 2009a, b) that quantify the mean plume CO_2/SO_2 ratios in individual (30 min long) Multi-GAS acquisition windows (Fig. 12a) find limited success in resolving clear gas changes prior to such modest (but still potentially harmful) explosions. This demonstrates the challenges in monitoring volcanoes that are continuously active and have multiple contemporaneously degassing vents exhibiting a range of activities (passive degassing, puffing, and regular Strombolian explosions). In such conditions, more elaborate post-processing techniques are required (Fig. 12b and c) that can track clear temporal switches in bulk plume chemistry, from low CO_2/SO_2 ratios during ordinary activity to high (>20) CO_2/SO_2 ratio phases in the weeks prior to the major explosions (Fig. 12c). These observations, combined with increasing plume CO_2 fluxes (Fig. 12d), corroborate models (Aiuppa et al. 2021) that basaltic paroxysms are caused by accumulation at depth of CO_2 -rich gas foams that initially leak passively (hence generating the gas precursor) and then catastrophically collapse to feed the explosion(s).

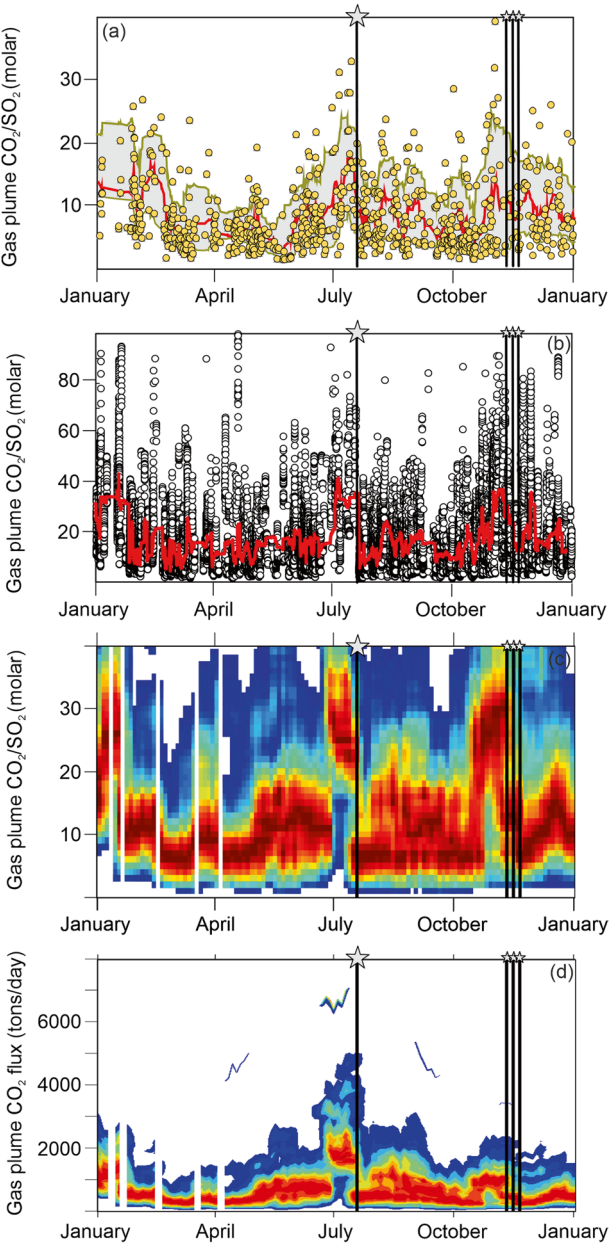
At closed-conduit volcanoes (Fig. 1b), including those that are topped by crater lakes

(Fig. 1d) or fumarolic fields (Fig. 1e), geochemists exploit the fact that the hydrothermal fluids released during volcano dormancy have far higher $\text{CO}_2/\text{S}_\text{T}$ ratios than magmatic gases (see Fig. 3) due to scrubbing of magmatic sulfur, either in the hydrothermal system or to the crater lake water (Stix and de Moor 2018). This process often causes elemental S deposition, and hence hydrothermal sealing, which can contribute to modulating (and triggering) volcanic activity (Christenson et al. 2015). As such, volcano reawakening is expected to be associated with a gradual decrease of $\text{CO}_2/\text{S}_\text{T}$ ratios as gases become increasingly magmatic in nature, switching from H_2S -dominated (hydrothermal) to SO_2 -dominated. This hydrothermal-to-magmatic gas transition has now been monitored at many volcanoes, such as in Alaska (Werner et al. 2011, 2013), at Turrialba in Costa Rica (de Moor et al. 2016a; Kern et al. 2022), and more recently at Agung in Indonesia (Syahbana et al. 2019) and at La Soufrière volcano, St. Vincent (Joseph et al. 2022). The timescales over which such hydrothermal-to-magmatic switches in gas composition take place vary widely, from decades (e.g., Vaselli et al. 2010) to weeks to days (de Moor et al. 2019). While decadal variations can easily be identified if a regular fumarole direct sampling program is in place, short-term precursors to eruption require continuous instrumental monitoring, and hence fall within the realm of the Multi-GAS. One of the most spectacular demonstrations has recently arisen at Poás volcano, where a clear progression, from hydrothermal (H_2S -dominated, high $\text{CO}_2/\text{S}_\text{T}$) to magmatic (SO_2 -dominated, low $\text{CO}_2/\text{S}_\text{T}$) gas, was detected by plume Multi-GAS observations prior to a phreato-magmatic eruption in 2017 (de Moor et al. 2019) (Fig. 13).

3.3 Crater Lake Monitoring

3.3.1 Volcanic Lake Geochemistry

Various classifications for volcanic lakes exist. Active or eruptive lakes are often characterized by high temperatures and salinity (Total



◀ **Fig. 12** Temporal variability of plume CO_2/SO_2 ratio at Stromboli volcano in 2020, as derived using different post-processing protocols. **a** Results of the ‘traditional’ CO_2/SO_2 ratio time-series analysis procedure (methodology of Aiuppa et al. 2009a, b). Each point (yellow circle) corresponds to the mean CO_2/SO_2 ratio in a 30-min-long Multi-GAS acquisition window. A ratio is calculated using an automated version of the code Ratiocalc (Tamburello 2015) if (i) SO_2 concentrations in the temporal window exceed a 4 ppmv concentration threshold, and (ii) the correlation coefficient between CO_2 and SO_2 concentrations is >0.6 (Pearson coefficient). The red line is a 15-day moving average, and the grey banded area (delimited by green lines) identifies ± 1 standard deviation around the mobile average. An apparent increase of the CO_2/SO_2 ratio is observed prior to four larger-than-normal (‘major’) explosions (identified by stars and black solid line). Note, however, a large scatter and spread of the ratios. **b** CO_2/SO_2 ratio time-series derived by applying (to the same concentration dataset used by protocol **a**) the ‘novel’ methodology of Aiuppa et al. (2021). An ad-hoc designed routine is used to scan the concentration dataset using a 60 s long moving window; a ratio is calculated if (i) SO_2 concentration is $>1\text{ppmv}$, and (ii) the correlation coefficient

(Pearson coefficient) between CO_2 and SO_2 concentrations is >0.9 . This methodology yields a higher resolution record of the compositional variations and considers a larger fraction of the acquired concentration dataset (note the four times lower SO_2 threshold, implying that more ratios are calculated). The red line is a 300-point moving average. **c** Temporal variation of the frequency distribution of the CO_2/SO_2 ratio, obtained from the ratios illustrated in panel **b** (see Aiuppa et al. 2021, for details). This figure conveys information on the temporal fluctuations of (i) the dominant (median) CO_2/SO_2 ratio levels (dark red colour tones) and (ii) the normalized spread of gas concentrations around the median (as indicated by orange/green/yellow/blue tones; blue tones correspond to the least frequent CO_2/SO_2 ratio populations). A clear, marked CO_2/SO_2 ratio increase (note the median values-dark red tones-at >20) is observed 15 to 20 days before the July and November major explosions. **d** Temporal variation of the plume CO_2 flux, calculated by multiplying the CO_2/SO_2 ratio time-series in (c) by the daily-averaged SO_2 flux (modified from Aiuppa et al. 2021, and Voloschina et al. 2023). A visible acceleration of the CO_2 flux is observed prior to the more voluminous July 2020 major explosion (Voloschina et al. 2023)

Dissolved Solids (TDS) >300 g/L: Rouwet et al. 2014), by efficient mixing, and by acidic pHs, although many exceptions exist, particularly for large lake systems (e.g., Rinjani or Taal lakes: Bernard et al. 2021). Where the inflow of acidic gases is minimal, active hydrothermal systems can discharge CO_2 -and H_2S -rich fluids, causing a slightly more elevated pH (2–3: Rouwet et al. 2014), with CO_2 present either as bubbles or in dissolved form (e.g., Bernard et al. 2021). Finally, the relative absence of acidic gases can produce near-neutral lakes, possibly enriched in CO_2 through CO_2 -enriched recharge. Dissolved CO_2 can either reach the surface through diffusion and/or bubbling or remain trapped in thermally stratified lakes, potentially leading to limnic eruptions when supersaturations of CO_2 exceed the hydrostatic pressure of the lake water column. More exhaustive registers of volcanic lake classification are provided in the reviews of Pasternack and Varekamp (1997), Varekamp et al. (2000) and Christenson et al. (2015).

Volcanic lakes have been studied for decades (e.g., Giggenbach 1974) and interest

intensified following the deadly eruptions of two Cameroonian lakes, Lake Monoun and Lake Nyos, in 1984 and 1986, respectively (e.g., Kling et al. 1987a, b). Over time, research efforts evolved from these CO_2 -dominated systems to focus on more acidic lakes fed by acidic gases. Initially focused on simply characterizing these systems and their hydrothermal systems (e.g., Kawah Ijen; Delmelle and Bernard 1994), scientists began to track their geochemical evolution with pioneer monitoring programs at Yugama (Japan, e.g., Takano 1987), Ruapehu (New Zealand, e.g., Giggenbach 1974), Poás (Costa Rica, e.g., Brantley et al. 1987) and, more recently by complementing geochemical data with geophysical and numerically based approaches (e.g., Christenson et al. 2010; Terada et al. 2011; Caudron et al. 2015).

The presence of a lake within a crater preserves geochemical markers which depend on the time that the water resides in the lake basin. We detail below some of the useful geochemical proxies that can be recorded within volcanic lakes.

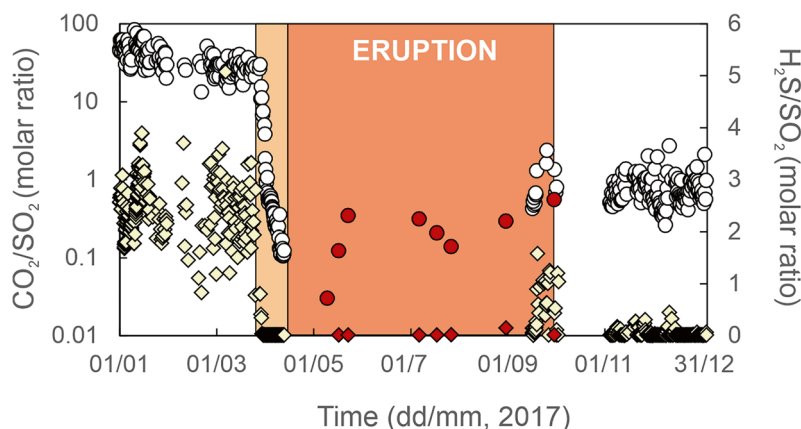


Fig. 13 Time-series of plume CO_2/SO_2 ratios (circles) and $\text{H}_2\text{S}/\text{SO}_2$ ratios (diamonds) in the plume of Poás volcano in 2017 (redrawn from data in de Moor et al. 2019), inferred from ground-based (white, yellow) and drone-based (red) Multi-GAS observations. Onset of phreatomagmatic activity in mid-April (and continuing

until September, dark orange area) was preceded (light orange shaded area) by orders-of-magnitude changes in both ratios, indicating a progression from hydrothermal-dominated (H_2S -rich) to magmatic-dominated (SO_2 -rich) gas signatures

3.3.2 Monitoring Crater Lakes Using Water

Monitoring of water compositions through time requires preliminary characterization of a lake and its underlying hydrothermal system. Such characterization usually consists of defining its geochemical and physical characteristics. Lake water composition reflects a delicate balance between gas inputs, fluid-rock interactions in the shallow hydrothermal system, and secondary mineral precipitation. Hence, prior to developing a dedicated monitoring program, researchers usually analyze the major cation and anion compositions of the system. Water compositions can reflect various degrees of reservoir mixing (Ohba et al. 2008). When possible, the residence time should be estimated, for instance through the concentration of tritium and its half life of radioactive decay (e.g., Rowe et al. 1995) or from the volume divided by the flow rate of fluids in or out of the lake, assuming steady-state conditions (Taran and Rouwet 2008; Rouwet et al. 2014; Taran et al. 2021).

Lake compositions often vary in three dimensions. It is usually advisable to avoid locations with meteoric water input and to closely monitor

meteorological conditions, or to rely on concentration ratios (see below); meteoric inputs or evaporation can strongly disturb the hydrological balance (Varekamp 2015). Physico-chemical conditions of the lake itself can change (e.g., stratification, oxygenation, temperature structure). Another critical parameter to monitor is therefore the lake temperature (Werner et al. 2006; Terada et al. 2008; Caudron et al. 2017). Thermal infrared (e.g., Oppenheimer 1993; Trunk and Bernard 2008) or in-situ measurements (e.g., Hurst et al. 2012) provide critical data to assess heat input.

Several absolute geochemical proxies have proven to be useful precursors to eruptions (e.g., cations, SiO_2 , but also SO_4^{2-} and Cl^- , as at Kusatsu Shirane; Ohba et al. 2008, and references therein). Most anions originate from magmatic-hydrothermal degassing (HCl , SO_2 , HF , CO_2 , H_2S) whereas cations derive mainly from rock leaching. Reactions between gas and water release protons and acidify waters, counterbalanced to some degree by the consumption of protons during metal leaching from volcanic rocks (Varekamp 2000) (Fig. 14).

Element ratios are less affected than element concentrations by external controls on water balance, such as dilution by rainfall or evaporation. Cl is usually considered one of the most conservative species whereas Mg^{2+} is a highly mobile element during water–rock interaction. Thus Mg/Cl has been interpreted as an indication of recent magma intrusion at depth (e.g. at Ruapehu; Giggenbach 1974). However, more recent studies have shown Cl escaping from lake water as a gas phase, suggesting that this proxy might be a less useful precursor in the most active and hot hyper-acidic crater lakes. The Mg/Cl ratio steadily increased at Poás from 1980s to 2006 as a consequence of evaporation, rather than indicating magmatic conditions (Rowe et al. 1992).

SO_4/Cl ratios should be also used with care. SO_2 and H_2S exhibit complex reactions and partitioning between the solid (minerals, elemental sulfur), solute, and gas phases (Rouwet et al. 2014). For instance, thiosulfates and polythionates can potentially be indicators of changes in volcanic activity but have only been detected at a handful of lakes; moreover, their speciation depends on a myriad of parameters that may be poorly constrained (temperature and $\text{SO}_2/\text{H}_2\text{S}$ ratio; Takano 1987). Due in part to this complex sulfur speciation, sulfur isotopic compositions are difficult to untangle and have rarely been used.

Lakes can also produce limnic eruptions when volcanic gases (CH_4 or CO_2) stored at depth become disturbed and are suddenly released at the surface. Such phenomenon occurred at Lake Nyos (Cameroon), where dense gases flowing downslope killed 1,700 people and 3,000 livestock in 1986 (Kling et al. 1987a, b). Sabroux et al. (1987) presented an idea to degas the bottom of lakes using pipes, which was later adopted to degas both Lake Nyos and Monoun (Cameroon) (Halbwachs et al. 2020). The same approach has been adopted at Lake Kivu since the 1960's to extract methane (Jones 2021).

Tracking CO_2 accumulation in Nyos-type lakes requires dedicated CO_2 monitoring strategies, such as lowering measurement probes and

sampling devices to depth along vertical profiles of the lake to maximum depth. Floating CO_2 chambers can be used to periodically monitor CO_2 at the surface (e.g., Mazot et al. 2014) and NDIR sensors (Bernard et al. 2021) to probe CO_2 concentration at depth. A lake-surface temperature measurement (Tassi and Rouwet 2014) or seismic monitoring (Rouwet et al. 2019) are other possible options. The reader is referred to Rouwet et al. (2014) for successful and less-successful examples.

An important constraint concerns the residence time; the time that water remains in the lake between entering as rainwater or vapor condensate and leaving the lake by evaporation, infiltration or overflow. When in equilibrium, water input and output are equal (Varekamp 2003) and the residence time can be estimated by dividing lake volume (m^3) by the flux of water (m^3/s) into the lake. Varekamp (2003) found that chemical contaminants can be flushed out after six residence times. This helps to define the relevant sampling frequency. Nonetheless, one should target the highest frequency possible, as phreatic eruptions can occur with minimal warning (e.g., Montanaro et al. 2022).

Springs seeping through volcanic edifices can also be useful for monitoring purposes, but also require in-depth characterization. Spring-chemistry ratios have been found to mimic crater lake compositions at Copahue (Agusto et al. 2017) but had distinct patterns at Poás (Rowe et al. 1995). Again, recharge time is critical and needs to be smaller than the time between the onset and the end of an event (Taran et al. 2021).

3.3.3 Monitoring Crater Lakes Using Gas

Volcanic gases can reach the lake floors in acid systems but tend to dissolve in neutral systems. Floating accumulation chambers are useful to periodically measure CO_2 emissions from a lake surface (e.g., Mazot et al. 2011; Bernard et al. 2021). Setting up continuous gas accumulation chambers remains extremely challenging, especially in the hyper-acidic crater lake systems.

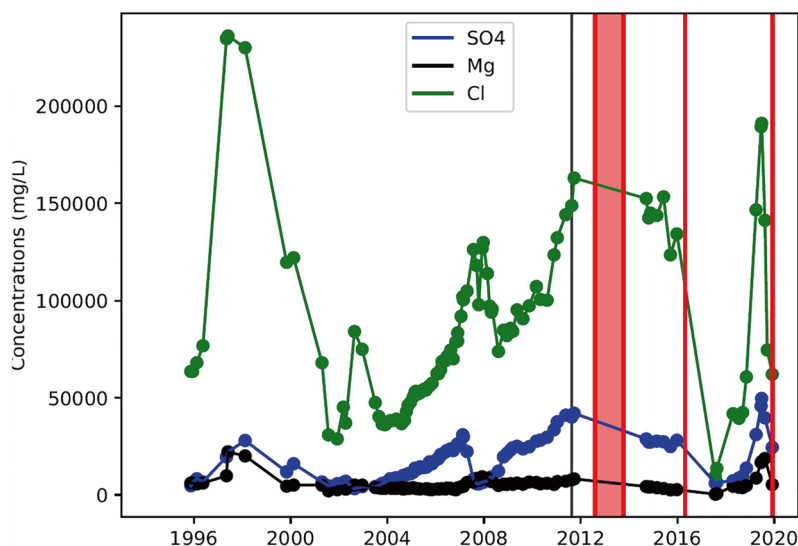


Fig. 14 Concentrations of SO_4^{2-} , Cl^- and Mg^{2+} at Whakaari/White Island volcano (site WI201, New Zealand). Data accessed from Geonet public data using github tutorial (https://github.com/GeoNet/data-tutorials/blob/main/FITS/FITS_data_access.ipynb). Red bars/areas identify eruptive episodes/periods. The black line

corresponds to an earthquake swarm described in Jolly et al. (2018). SO_4^{2-} , Cl^- concentrations reflect magmatic volatile transfer into the lake. Mg^{2+} is leached from the host rock and behaves conservatively in hyper-acidic solutions (Giggenbach 1974). The reader is referred to Christenson et al. (2017) for more information

This difficulty can be bypassed by using gas-specific sensors (e.g. MultiGAS; cfr. 3.2.3) that have successfully detected changes in volcanic gas emissions prior to phreatic eruptions at volcanic lakes (de Moor et al. 2016b, 2019; Battaglia et al. 2019) and currently constitute the best strategy for monitoring purposes. The lake plume CO_2/SO_2 ratio decreased, approaching magmatic values, in the few days preceding phreatic eruptions at Poás volcano. At Poás, hyperacidity inhibits scrubbing and CO_2 behaves as an inert gas species. At Taal Main Crater Lake, a miniaturized Non Dispersive Infrared Sensor detected an increase in CO_2 emissions one year before a phreato-magmatic eruption in January 2020 (Bernard et al. 2021).

Hydroacoustic measurements can be sensitive to gas bubbles. Hydrophones have been installed in a few volcanic lakes to monitor gas levels (e.g., Vandemeulebrouck et al. 2000) in various frequency bands. Recent studies have examined continuous hydroacoustic monitoring

at Yellowstone (Caudron et al. 2022a, b) and Laacher See (Caudron et al. 2020). Another approach is to periodically survey lakes using echosounders to detect bubble flare venting (Caudron et al. 2012; Hernández et al. 2017).

3.4 Monitoring Soil Degassing: CO_2 and Other Species

3.4.1 Methods in Soil CO_2 Degassing

Soil diffuse degassing is the main CO_2 degassing mechanism at many dormant/quiescent volcanoes. Most diffuse degassing studies in the last three decades have focused on CO_2 . Other gas species, such as He, H_2 and ^{222}Rn have also been detected in diffuse degassing areas (e.g., Heiligmann et al. 1997; Rodriguez et al. 2015; Neri et al. 2016; Alonso et al. 2022), using more expensive and time-consuming techniques compared with the methods applied to measure CO_2 . As far as we are aware, the first diffuse degassing measurements ever done on an active

volcano were conducted by Sato and McGee (1980), who detected H_2 on the flanks of Mount St. Helens in 1980.

The importance of CO_2 for volcano monitoring (e.g., Baubron et al. 1990; Notsu et al. 2006), together with the development of several ‘user-friendly’ CO_2 methods, makes this gas widely measured in diffuse degassing environments. Two main flux methodologies have been used to measure CO_2 diffuse degassing: the accumulation chamber (Chiodini et al. 1998) and the dynamic concentration method (Gurrieri and Valenza 1988).

Chamber methods were initially used on agricultural fields to measure soil respiration (e.g., Kanemasu et al. 1974; Parkinson 1981), and since the early 1990s this methodology has been applied in hydrothermal-volcanic environments (e.g., Chiodini et al. 1998; Werner et al. 2019). The accumulation chamber is a direct and passive method based on the rate of CO_2 concentration increase inside a known chamber volume, which is placed face-down on the surface (Fig. 15a) (Chiodini et al. 1998). Application of this method does not require any specific assumptions about the physical properties of the soil (Carapezza and Granieri 2004).

In the dynamic concentration method, the gas is pumped at a constant rate from the soil (at a depth of around 50 cm) until the CO_2 concentration reaches a constant value (Gurrieri and Valenza 1988). This method requires information about the physical characteristics of the soil, such as permeability, to convert the dynamic concentration into a flux value (Camarda et al. 2006).

Due to the easier and faster methodology, the accumulation chamber has become the prevailing method used worldwide. It has been used to measure both spatial (Fig. 15b) and temporal CO_2 flux variations (e.g., Chiodini et al. 1998, 2001, 2003; Hernández et al. 1998; Cardellini et al. 2003, 2017; Granieri et al. 2003, 2010; Lewicki et al. 2005; Viveiros et al. 2008, 2010; Oliveira et al. 2018; Werner et al. 2019). The accumulation chamber has also been adapted to lakes using a floating device (e.g., Mazot et al. 2011; Pérez et al. 2011; Bernard et al. 2021).

Both methodologies measure CO_2 independent of its origin. In order to identify the different sources of CO_2 released from soils, Chiodini et al. (2008) combined gas sampling for carbon ($\delta^{13}C$) isotopes with CO_2 flux measurements. This methodology has been applied in various degassing areas (Viveiros et al. 2010, 2020; Parks et al. 2013) and contributes to identifying a threshold for the deep-derived CO_2 emissions. Recently, several studies coupled soil CO_2 fluxes, $\delta^{13}C$ and radon emissions to discriminate deep and shallow gas components (Parks et al. 2013; Bini et al. 2020) and constrain the depth of degassing (Girault et al. 2022).

Permanent automatic CO_2 diffuse degassing stations (Fig. 15c) have been set up by volcano observatories in the last few decades. Italian volcanoes have some of the longest CO_2 time series, with stations installed on Etna (e.g., Badalamenti et al. 2004; Gurrieri et al. 2008; Liuzzo et al. 2013), Stromboli (e.g., Carapezza et al. 2004; Inguaggiato et al. 2017, 2021), Vulcano (e.g., Inguaggiato et al. 2022), Vesuvius and Campi Flegrei (e.g., Granieri et al. 2010) and Colli Albani (e.g., Tarchini et al. 2022). Long CO_2 time series have also been recorded at Mammoth Mountain, USA (e.g., Rogie et al. 2001), Aso Volcano, Japan (Morita et al. 2019), Piton de la Fournaise, La Réunion, France (Boudoire et al. 2017), Canary Islands, Spain (e.g., Hernández et al. 2012; Pérez et al. 2012), and Azores, Portugal (Viveiros et al. 2008, 2015; Oliveira et al. 2018).

Data recorded by these networks show that meteorological variables may interfere with as much as 50% or more of the gas released from soil (e.g., Granieri et al. 2003; Viveiros et al. 2008, 2015; Hernández et al. 2012; Laiolo et al. 2016; Oliveira et al. 2018; Morita et al. 2019; Jentsch et al. 2021; Tarchini et al. 2022). These influences may drive spiky and long-term (seasonal) variations in the soil gases (Fig. 15d), which can be misinterpreted as changes occurring at depth (e.g., Gerlach et al. 2001; Viveiros et al. 2014). Barometric pressure, air and soil temperature, wind speed, soil water content, and rainfall (Giammanco et al. 1995; Granieri et al. 2003, 2010; Liuzzo et al. 2013; Viveiros et al.

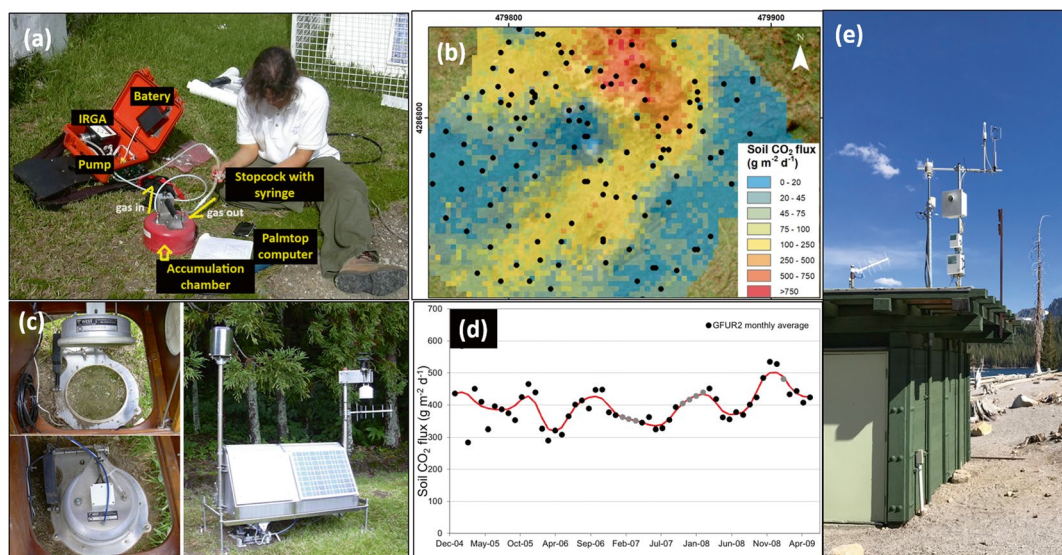


Fig. 15 Photo of soil CO₂ flux instrumentation and examples of spatial and temporal data. **a** Coupled soil CO₂ flux measurement and carbon isotopic sampling using a portable instrument with accumulation chamber (IRGA stands for InfraRed Gas Analyser). Data sampling follows the methodology illustrated in Fig. 2 of Chiodini et al. (2008). **b** Interpolated soil CO₂ degassing map showing the location of the sampling sites (black dots). Data from Viveiros et al. (2020) and

interpolation followed the sequential Gaussian simulation. **c** Permanent soil CO₂ flux station showing the accumulation chamber and the meteorological sensors. **d** Soil CO₂ flux monthly averages recorded at GFUR2 permanent station where seasonality is observed. The red line represents the data smoother defined in Velleman (1980). **e** Eddy covariance system operating at Mammoth Mountain (USA) since 2014 (credits: Jennifer Lewicki, USGS)

2014, 2015; Laiolo et al. 2016; Oliveira et al. 2018; Morita et al. 2019; Bénard et al. 2023) are among the variables that impact gas emissions. External variables may affect each station site in different ways, depending on specific characteristics of the location such as topography, water-table depth, tectonic features, and heterogeneous geology (Viveiros et al. 2008, 2014; Liuzzo et al. 2013). This emphasizes the need to have meteorological sensors coupled to the gas stations and to implement repeated spatial surveys on days with similar and stable meteorological conditions (e.g., Lewicki et al. 2005; Viveiros et al. 2020).

Filtering the soil CO₂ time series from external interferences is essential before establishing correlations with volcanic processes. Ideally, two years of data acquisition during quiet periods of activity would allow filtering seasonal trends from the CO₂ time series, but if not possible, at least one entire year would be needed.

Several statistical techniques (including regression, principal components, spectral analysis and wavelets) have been applied to isolate deep inputs to the soil gases (e.g., Granieri et al. 2003; Viveiros et al. 2015; Laiolo et al. 2016; Boudoire et al. 2017; Oliveira et al. 2018; Scudero et al. 2022). External influences affect not only CO₂ emissions but also other diffusely released gases, such as radon (e.g., Neri et al. 2016).

The chamber method is limited to measurements on a small spatial scale (<1m²), and continuous measurements are restricted to one or a few sites. The eddy covariance method, a micrometeorological technique used to measure CO₂, is a complementary technique that has yielded promising results, owing to its capacity to monitor significantly larger areas. This technique has been applied at Yellowstone (Werner et al. 2000), Solfatara (Werner et al. 2003), and Mammoth Mountain (e.g., Anderson and Farrar 2001; Lewicki et al. 2008; Lewicki 2021) and

has provided insights about the correlation between increases in CO₂ flux and volcanic activity.

3.4.2 Correlation Between Soil CO₂ and Volcanic Activity

Despite the influence of environmental variables, a correlation between CO₂ flux increases and periods of heightened volcanic activity has been established at several volcanoes. Precursory flux anomalies were detected, in some cases, by automated monitoring stations (Pérez et al. 2012; Inguaggiato et al. 2021; Boudoire et al. 2017; Morita et al. 2019). Other studies based on repeated spatial flux surveys have documented expansion in anomalous degassing and an increase in background CO₂ (Werner et al. 2014; Cardellini et al. 2017).

Significant increases in soil CO₂ fluxes were observed at Stromboli volcano prior to paroxysmal explosions. Carapezza et al. (2004) discussed the increases in CO₂ fluxes recorded by an automated station one week before a violent paroxysm on 5 April 2003. Inguaggiato et al. (2011, 2021) documented similar increases associated with the 2017 and 2019 paroxysms. Laiolo et al. (2016) argued that permanent stations are needed at Stromboli to detect precursory anomalies.

Several studies have shown a correlation between soil CO₂ emissions and volcanic activity on Etna. These studies started in the early 1990s, and Giammanco et al. (1995) reported diffuse CO₂ increases in stations located on the flanks of Etna a few months before the onset of the 1991–93 eruption. These authors also discussed the decrease in CO₂ degassing on the flanks during the eruptive period, when degassing seemed to be concentrated in the summit area. Badalamenti et al. (2004) showed that in the period between November 1997 and September 2000, anomalous soil CO₂ degassing anticipated summit eruptions. Cannata et al. (2010) suggest that soil CO₂ flux variations preceded volcanic tremor by about 50 days between November 2002 and January 2006. Ten years of permanent, automatic CO₂ monitoring

at Etna show that, in most cases, CO₂ anomalies preceded volcanic activity (Liuzzo et al. 2013). Nevertheless, these authors emphasize the importance of filtering soil CO₂ fluxes and taking into account site-dependent behaviour.

Six months before the 31 March 2000 Usu Volcano eruption, an increase in CO₂ was detected during surveys carried out at the summit caldera (Hernández et al. 2001). Data recorded by a permanent CO₂ flux station installed at Aso volcano (Japan) between January 2016 and November 2017 showed the interference of environmental parameters on the gas flux. However, soil CO₂ flux increases also suggested magmatic CO₂ input, and correlations were established with tremor and SO₂ fluxes, especially before and after the 8 October 2016 phreatomagmatic eruption (Morita et al. 2019).

At Piton de la Fournaise (La Reunion, France), increasing soil CO₂ fluxes preceded the 2014 reactivation of the volcano by three months, after a 41-month rest period (Boudoire et al. 2017). Taal Volcano (Philippines) erupted on 12 January 2020 after a 43-year quiescence, and Pérez et al. (2022) showed positive trends in diffuse emission from the crater lake and in soil CO₂ fluxes measured at an automated station that suggest magma recharge to the system years before resumed eruptive activity.

Even in areas with low CO₂ degassing, subtle increases in soil CO₂ fluxes may be detected, as observed before the 2011 El Hierro submarine volcanic eruption (Pérez et al. 2012). Melián et al. (2014) showed that the results from 8 years of permanent monitoring at El Hierro were in agreement with spatial surveys and advocated combining continuous studies with discrete surveys in volcano monitoring programs.

Diffuse CO₂ monitoring has proved to be a powerful tool for detecting and interpreting pre-eruptive processes related to dike intrusion and/or movement of fluids. For instance, Campi Flegrei caldera has shown signs of unrest over the past decades (e.g., Chiodini et al. 2003, 2021). The spatial CO₂ anomaly tripled from 2003 to 2016 (Cardellini et al. 2017), consistent with the injection of magmatic fluids into

the hydrothermal system, potentially raising fluid pressure and, in turn, forcing condensation within the vapor plume feeding the Solfatara emission.

At Vulcano Island, spatial and temporal increases in summit degassing and in soil CO₂ fluxes were detected during the second half of 2021 and in 2022. These anomalies were attributed to input of volatiles from a new and CO₂-rich magma batch (Inguaggiato et al. 2022).

Mammoth Mountain has experienced several periods of unrest since 1989, with seismicity and high degassing which caused a large tree-kill area (e.g., Farrar et al. 1995; Rogie et al. 2001; Werner et al. 2014). Monitoring between 1995 and 2013 showed that peaks in CO₂ emissions emerge 2 to 3 years after seismic swarms. Seismicity is thus interpreted as associated with an influx of magmatic fluids into a shallow hydrothermal reservoir, causing pressurization events and time-delayed CO₂ leakage (Werner et al. 2014). At Teide Volcano (Canary Islands), variations in 49 soil CO₂ flux maps generated between 2000 and 2016 was linked to seismic activity, (Hernández et al. 2017), suggesting, as at Mammoth, an association with magma degassing and magmatic fluid injection.

Most of the reported anomalies highlighted above represent increases in soil CO₂ fluxes preceding volcanic activity and/or unrest periods. However, at Furnas Volcano, Viveiros et al. (2014) did not observe any increase in CO₂ fluxes, but rather changes in the periodic signal of the CO₂ time series potentially correlated with local seismic activity.

3.5 Monitoring Volcanoes Using Groundwater

Changes in groundwater systems can be both a valuable signal during volcanic unrest and a major source of interference in other volcano-monitoring data streams. Advection of heat and mass by groundwater affects and often dominates the thermal and chemical regimes of volcanoes. Conversely, magma influences

groundwater pressures, chemistry, and temperatures. Linkages between groundwater flow and mechanical deformation are suggested by observations that volcanoes deform in response to changes in water-table elevation and that seismicity can often be related to fluid pressures and boiling.

Subsurface water can act as a trigger and lubricant for lahars and as a propellant in phreatic eruptions. However, while groundwater itself can be an agent of unrest and even eruption, it is equally important to understand how key geophysical (seismic and geodetic) and geochemical (gas) signals from magma are modulated by groundwater systems.

This section focuses on changes in groundwater pressure, chemistry, and temperature associated with volcanic unrest. We will frame our discussion in the context of the hypothetical magmatic-hydrothermal system depicted schematically in Fig. 16, a simplified version of Fig. 1b.

3.5.1 Background and Motivation

Changes in groundwater pressure, chemistry, and temperature remain, in general, poorly studied phenomena at volcanoes (Sparks 2003; National Academy of Sciences 2017)—despite the fact that the potential for hydrologic changes to provide warning of impending eruptions has been repeatedly demonstrated. At Mount Vesuvius (Italy), in 1631 A.D., several water wells 5 to 7 km from the summit were reported to be dirty, increasingly salty, or dry several weeks before a major eruption (Rolandi et al. 1993; Rosi et al. 1993; Bertagnini et al. 2006). Several later eruptions of Vesuvius were similarly preceded by changes in well-water levels (Bertagnini et al. 2006). Other examples of precursory hydrologic changes include significant decreases in flow rate from springs ~8 km from the summit of Mayon (Philippines) before most eruptions in the twentieth century (Newhall et al. 2001); systematic water-level changes in two wells within 1 km of the vent several months prior to the 2000 eruption of Usu Volcano (Japan) (Shibata and Akita 2001); and increases in CO₂, H₂, and He contents in

shallow wells before the 2002–2003 eruption of Stromboli volcano (Italy) (Carapezza et al. 2004). During the 2008 eruption of Nevado del Huila, Colombia, relatively minor phreatomagmatic eruptions were accompanied by expulsion of up to 300 million cubic meters of groundwater from fissures high on the volcano (Worni et al. 2012), generating large lahars. River monitoring at Mount Redoubt in 2009 allowed Werner et al. (2012) to recognize that groundwater was unable to absorb the high flux of volcanic gas, and that a high CO_2/SO_2 precursor signal had been evident for five months prior to the eruption. Relatively high-resolution $^3\text{He}/^4\text{He}$ time series from springs on the flanks of Etna volcano (Italy) reveal that the main eruptive episodes are preceded by widespread, synchronized increases in the $^3\text{He}/^4\text{He}$ ratio (Paonita et al. 2016). Similarly, significant increases in helium emissions from soil and $^3\text{He}/^4\text{He}$ ratios in groundwater on El Hierro Island (Canary Islands, Spain) were observed prior to a nearby submarine eruption in 2011–2012 (Padrón 2013). The 2014 Ontake phreatic eruption was also anticipated by large He isotope changes over the preceding decade (Sano et al. 2015). Both distal volcano-tectonic earthquakes (White and McCausland 2016; Coulon et al. 2017) and phreatic eruptions (e.g. Yamaoka et al. 2016) are widely attributed to fluid-pressure changes in aquifers and hydrothermal systems.

Such examples demonstrate the potential for groundwater monitoring to augment and inform other data streams. Although quite numerous, relatively few volcano-hydrology anomalies are well-documented, and many are essentially anecdotal (Newhall et al. 2001). This reflects the fact that high-resolution time series remain rare.

3.5.2 Changes in Groundwater Pressure, Chemistry, and Temperature During Volcanic Unrest

During volcanic unrest, processes such as intrusion of new magma, release of magmatic volatiles, and seismicity cause changes in groundwater pressure, chemistry, and temperature. Changes in groundwater pressure can

propagate relatively fast and far. In a homogeneous medium, the distance L over which significant pressure changes can propagate in time t is $L=(tD)^{1/2}$ for radial flow and $L=2(tD)^{1/2}$ for linear flow, where $D=k/[n\mu_f(\beta_f+\beta_r)]$ is the hydraulic diffusivity and k is permeability, n is effective porosity, μ_f is the dynamic viscosity of the fluid, β_f is the compressibility of the fluid, and β_r is the compressibility of the porous medium. These relationships define the time t at which the pressure change at L will be 1/10 of the pressure change at the pressure source or sink ($L=0$). Permeability k is the key controlling variable because of its large range of variation in common geologic media (e.g. Gleeson and Ingebritsen 2017). In magmatic-hydrothermal systems (Fig. 16), the fluid compressibility β_f is also important, because the effective compressibility of a two-phase (boiling) mixture is about 30 times larger than that of pure steam at the same temperature and 10^4 times larger than that of liquid water at the same temperature (Grant and Sorey 1979). Effective values of D in the tectonically active upper crust are such that, in some instances, fluid-pressure pulses appear able to migrate rapidly, on the order of km/day.

Migration of solutes away from a source is much slower, limited to the fluid-particle velocity $v=q/n$, where q is the volumetric groundwater flow rate ($\text{m}^3/(\text{m}^2\text{--s})$) and the effective porosity n is unitless. Fluid-particle velocities in groundwater systems are such that solute migration rates larger than km/yr are rare, and the migration of reactive solutes will be further retarded by water–rock reactions. This suggests that we should not normally expect magmatically sourced solutes to migrate quickly towards distal locations. However, during unrest, seismic activity can increase permeability, potentially linking formerly separate fluid reservoirs and changing groundwater chemistry quasi-instantaneously anywhere in our hypothetical flow system (Fig. 16).

Heat advection is typically orders of magnitude slower than solute advection, governed by q rather than q/n and further retarded by the very large thermal inertia of the water–rock system. But again, the temperature of groundwater anywhere in our hypothetical flow system can

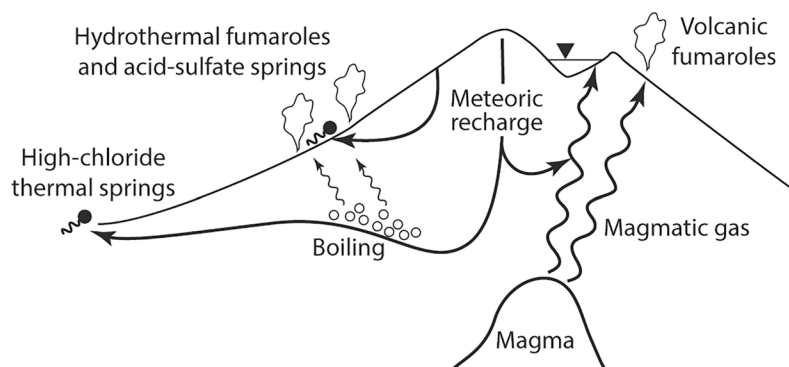


Fig. 16 Conceptual model of a magmatic-hydrothermal system showing three types of hydrothermal-discharge features: high-chloride springs; hydrothermal fumaroles and associated acid-sulfate springs; and volcanic fumaroles. In the boiling zone, phase separation takes place because of the density difference between liquid water

and its vapor (steam), with vapor and associated volatile constituents (such as CO_2 , H_2S) rising to discharge in acid-sulfate springs, liquid water and other solutes (such as Cl and silica) flowing laterally to discharge from near-neutral-pH springs. In natural systems, the actual scale of phase separation can range from meters to ~ 10 km

change nearly instantaneously if seismic activity increases permeability, thereby short-circuiting existing fluid-flow patterns. Further, even very proximal and localized (near-magma) heating can cause thermally driven fluid-pressure changes that propagate rapidly to distal locations. This is a reminder that pressure, chemistry, and temperature changes in groundwater systems are closely coupled.

Pressure. Both distal and proximal fluid-pressure changes are of interest during volcanic unrest and eruption. Distal volcano-tectonic (dVT) seismicity typically precedes eruption at long-dormant volcanoes by days to years, and may reflect magma-induced fluid-pressure pulses that intersect critically stressed faults (White and McCausland 2016). Numerical modeling designed to test this hypothesis demonstrated that propagation of potentially causal pressure changes ($\Delta P > 0.1$ bars) to the mean dVT location (6 km lateral distance, 6 km depth) is favored by channelized groundwater flow, high magma devolatilization rates, and permeabilities similar to those found in geothermal reservoirs ($k \sim 10^{-16}$ to 10^{-13} m²) (Coulon et al. 2017). With higher permeabilities, pressures dissipate too readily, and sufficiently elevated pore-fluid pressures are not achieved. With lower

permeabilities, proximal pressure changes do not migrate to distal locations over the relevant timeframe. If groundwater flow is channelized, magma-induced thermal pressurization alone can generate $\Delta P > 0.1$ bars at distal locations for all permeabilities in the range 10^{-16} to 10^{-13} m². This implies that monitoring hydrological systems to document pressure changes is potentially useful. The causal pressure changes may be both deep and localized, such that capturing them would be difficult and expensive. However, more diffuse signals might be regionally observable; transients in geothermal wells have been correlated to subsurface processes (e.g. Jonsson et al. 2003) and the 2000 Usu eruption was associated with a well-documented water-level rise (Matsumoto et al. 2002). In the absence of extensive subsurface monitoring systems, we remain cautiously optimistic on this point.

Consistent with observational data (e.g. Lu et al. 2002), the dVT modeling also yielded proximal fluid-pressure changes that, in certain scenarios, would be sufficient to cause surface deformation (Coulon et al. 2017). In order to be useful in an evolving volcanic-unrest situation, geodetic data would have to cover proximal zones and be available in near-real-time. One compelling example is the 2014 phreatic eruption of Mount Ontake, Japan. In 1979, the

first recorded Ontake eruption in human history occurred, a VEI 2 event; phreatic eruptions also occurred in 1991, 2007, and 2014, the latter a tragedy that claimed the lives of at least 58 hikers and was the worst volcanic disaster in Japan since the 1926 phreatic eruption of Mt. Tokachidake. Teams of Japanese scientists (Yamaoka et al. 2016) concluded that it is possible, perhaps likely, that the recent cycle of phreatic eruption at Ontake reflects repeated pressurization and breaching of the shallow hydrothermal system (although different interpretations have also been proposed; Kato et al. 2015; Sano et al. 2015). Diminished fumarolic activity prior to eruption may reflect a period of sealing and pressurization of the shallow hydrothermal system; fractures begin to open or shear when fluid pressure is sufficiently elevated. Monitoring and forecasting capability might be improved by deploying additional geophysical and geochemical-monitoring capabilities in the near vicinity of the summit crater. In 2014 there were midterm (days) changes in seismic activity prior to the eruption, but the implications of these changes were regarded as ambiguous in real time. And although no geodetic deformation was detected in real time, retrospective analysis of geodetic data (Miyaoaka and Takagi 2016) confirmed minor near-summit deformation. Retrospective seismic analysis identified relative seismic velocity (dv/v) changes 5 months prior to eruption, and over the same time period, there is a striking correlation between the dv/v time-series and the pressure changes observed in a sealed well 10 km southwest of the summit (Caudron et al. 2022a, b). The seismic velocity changes would have been hard to interpret in real-time as dv/v also varies seasonally. An improved local geodetic network, or analysis of InSAR data, might have facilitated near-real-time interpretation of midterm seismic and geodetic changes. There is a compelling need to improve our abilities to forecast such phreatic eruptions, as the deadly 2019 White Island eruption (22 fatalities) was also tentatively attributed to breaching of a hydrothermal seal, with pressurization of the system in the week before the

eruption and cascading seal failure in the 16 h prior (Ardid et al. 2022).

Chemistry. Here we will consider the contrasting implications of two well-documented chemical anomalies associated with volcanic unrest, one proximal and one distal. An example from South Sister, Oregon, involves proximal (near-magma) behavior during volcano unrest, whereas an example from Lassen, California, documents distal changes that affected water quality up to 75 km downstream.

In 2000–01 a geochemical investigation of springs near the Three Sisters volcanoes, Oregon, was conducted in response to detection of crustal uplift (Fig. 17). Springs near the center of uplift showed $^3\text{He}/^4\text{He}$ ratios $>7R_A$ (R_A is the ratio in air) and were found to transport in total ~ 16 MW of heat, ~ 180 g/s (16 tonnes/day) of magmatic carbon (as CO_2), and ~ 10 g/s of chloride, well above typical levels in streams and springs of the region (Evans et al. 2004). The maximum measured R_A value of 8.6 remains the highest ever measured in the Cascades or Aleutian volcanic arcs, despite the low-temperature ($<11.2^\circ\text{C}$) and dilute ($\text{Cl} < 20.5$ mg/L) nature of these springs. Further, the occurrence of sulfate and bicarbonate anomalies in higher-elevation springs, versus chloride anomalies in lower-elevation springs (Fig. 15, lower panel), suggests boiling and phase separation at depth (as in Fig. 16). These anomalous geochemical conditions clearly reflect the influence of underlying magma. However, the geochemical anomalies may predate the onset of uplift in 1998, because the total anomalous chloride load in 2001 was identical to the 10 g/s measured in 1990 (Ingebritsen et al. 1994). Chloride concentration and temperature are highly correlated within localized spring groups in the area of uplift (Evans et al. 2002), and ^3He and chloride concentrations are highly correlated throughout the Three Sisters region (Crankshaw et al. 2018). We can infer that the geochemical anomaly is relatively stable and longstanding, likely reflecting the effects of past intrusions. Although the geochemical anomaly

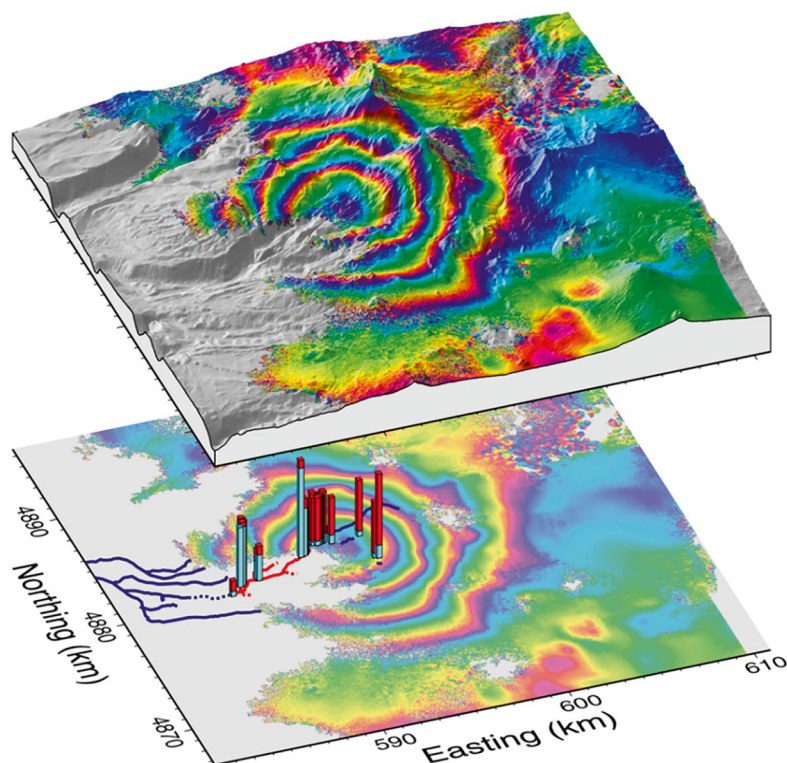


Fig. 17 (Top) 1996–2000 interferogram of South Sister, Oregon, draped over a 30-m digital elevation model. (Bottom) Geochemical data on top of the 1996–2000 interferogram. The columns show chloride and sulfate concentrations at sampled springs. The lengths of the cyan columns depict chloride concentration (0.6 to 18.6 mg/L versus a background of 0.2 to 0.7 mg/L). The

lengths of the red columns show SO_4/Cl ratios (0.2 to 2.8). Blue lines highlight stream reaches with steady or decreasing Cl concentration in a downstream direction. Red lines highlight reaches within which Cl concentrations increase downstream. The interferogram color cycle from violet to red corresponds to a range increase of 28.3 mm. After Wicks et al. (2002)

is proximal, in the sense that it overlies a likely magmatic intrusion, over the timescale of observation it is essentially decoupled from the early 2000s uplift and subsequent minor earthquakes. The persistence and stability of the geochemical anomaly also suggests, quite strongly, that episodes of magmatic intrusion have been more common in this area than the age of local eruptive vents might imply.

In November 2014 a distal earthquake swarm near Lassen Volcanic National Park, California, which included the largest earthquake in the area in more than 60 years, was accompanied by a rarely documented outburst of hydrothermal fluids (Ingebritsen et al. 2015). The Lassen hydrothermal system exhibits large-scale phase separation, with acid-sulfate and high-chloride

springs (cf. Fig. 18) separated by ~10 km. The 2014 earthquake swarm was at a distal location very close to the main high-chloride spring groups. In response to eyewitness accounts of water-level oscillation, increased turbidity and flow, and new areas of steaming ground, the U.S. Geological Survey immediately began monitoring the total outflow of hot water, and established that the outflow briefly doubled, peaking 40–50 days after the largest seismic event and decaying to preseismic levels within ~120 days (Fig. 18, upper panel). The high-chloride springs at Lassen also normally discharge ~6 tonnes/yr of arsenic and, rather surprisingly, high arsenic concentrations and fluxes were documented ~75 km downstream during the period of unrest (Fig. 18, lower panel).

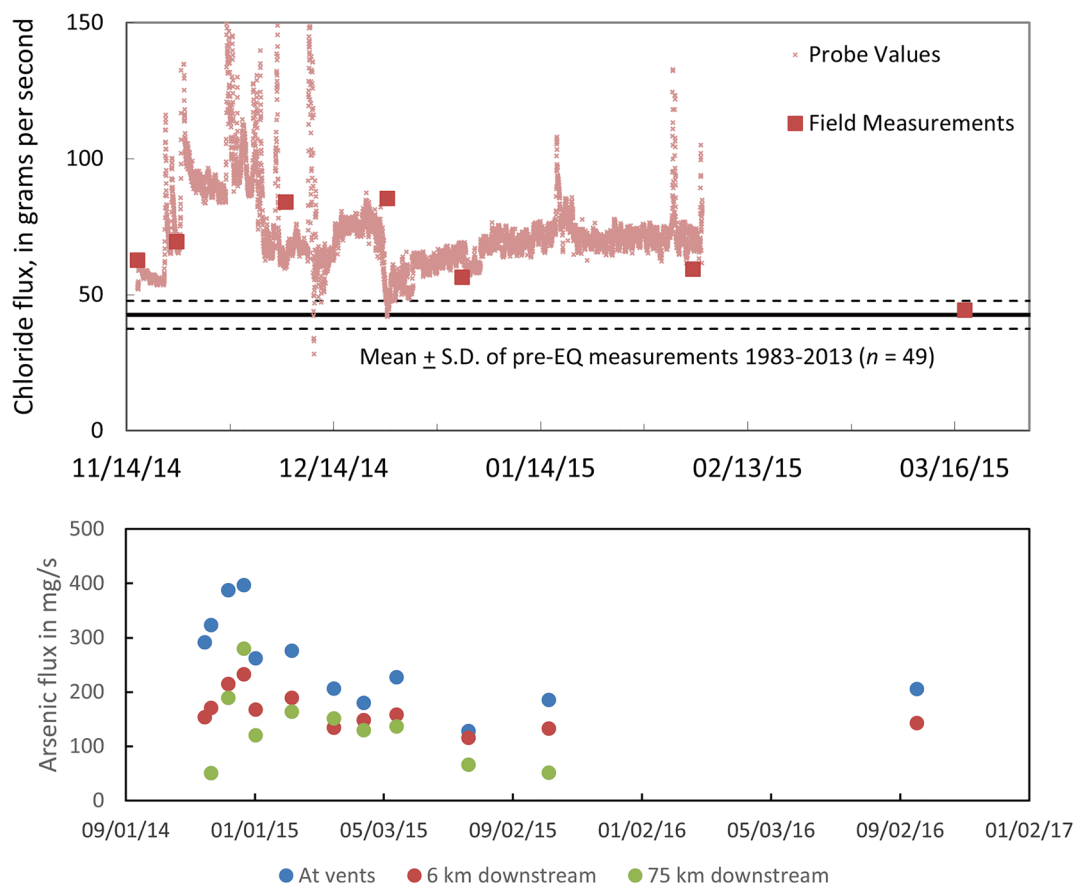


Fig. 18 (Top) Chloride-flux record capturing outflow from the Lassen hydrothermal system from November 2014 to May 2015. Horizontal lines are mean $\pm$ standard deviation of previous discrete measurements of chloride flux from 1983–2013 (42.6 ± 5.2 g/s [Cl^-], $n=49$). ‘Field measurements’ are based on discharge measurements concurrent with water sampling, whereas ‘probe values’ are based on pressure (water level) and electrical conductivity (used as a proxy for Cl^-) recorded every 15 min. Error associated with individual field measurements is 5–10%. Probe values are less accurate but reveal high-frequency variability associated with precipitation

events that may reflect flushing of hydrothermally sourced Cl^- from local, near-surface storage. From Ingebritsen et al. (2015). (Bottom) Downstream arsenic fluxes during and after volcanic unrest in 2014–15. Fluxes at vents are inferred based on assumed constant vent concentrations of Cl^- and As. Fluxes 6 and 75 km downstream are measured values. Potentially problematic increases in downstream arsenic flux were also documented in Japan following the 2018 eruption of Mount Iou (Hama et al. 2023). From Ingebritsen and Evans (2019)

Observed stream arsenic concentrations were as high as 200 g/L at 6 km downstream of the hot-spring vents and 36 g/L at 75 km downstream, well in excess of the 10 g/L regulatory standard for drinking water.

Although the upward-migrating (~ 0.5 km/day) Lassen earthquake swarm itself may have reflected movement of endogenous $\text{H}_2\text{O}-\text{CO}_2$ fluids, there is no evidence that such fluids

emerged at the surface, as hot-spring vent chemistry remained essential unchanged. Instead, shaking from the modest-sized (maximum moment magnitude $M_w=3.85$) but nearby earthquakes caused near-vent permeability increases that triggered increased outflow of fluids already present and equilibrated in the local hydrothermal aquifer. Thus, the hydrothermal response to this episode of volcanic unrest at

Lassen—in contrast to our Three Sisters example—was essentially instantaneous.

Temperature. In the absence of permeability changes that connect formerly separate reservoirs, we expect thermal responses to be slow relative to changes in pressure and chemistry. Nonetheless, statistical analysis of satellite-based long-wavelength ($10.78\text{--}11.28\ \mu\text{m}$) infrared data showed that the most recent magmatic or phreatic eruptions at five different volcanoes—including Ontake—were preceded by long-term (years), large-scale (tens of square kilometers) increases in radiant heat flux (up to $\sim 1\ ^\circ\text{C}$ in median radiant temperature) (Girona et al. 2021). These long-term pre-eruptive variations were proposed to reflect subsurface magmatic–hydrothermal fluid interactions, possibly enhanced by diffuse degassing.

Here we will focus on one particular example in which the thermal evolution of the water–rock complex was key to modeling and forecasting syneruptive behavior. During the early stages of the 2018 Kīlauea eruption, the conceptual model of Stearns (1925), based on the explosive 1924 Kīlauea eruption, was highly influential. This model postulates that explosions are triggered by liquid water inflow into a recently vacated magma conduit. Modern quantitative modeling approaches, supplemented by hydrogeologic

data—both unavailable in 1925—yielded a more nuanced view. Numerical modeling demonstrated that liquid water inflow would likely be delayed by months to years owing to the inability of liquid water to transit a zone of very hot rock surrounding the vacated magma conduit (Fig. 19; Hsieh and Ingebritsen 2019). The numerical modeling employed a high-temperature (to $1200\ ^\circ\text{C}$), multiphase simulator (<https://volcanoes.usgs.gov/software/hydrotherm/>) and was constrained by hydraulic-property and water-level data from a 1262-m-deep research drillhole on Kīlauea summit. Numerical modeling was successful in predicting both the timing of the first water entry (14.5 months post-collapse) and the rate of filling (10 s of kg/s) of a short-lived (2019–20) water lake in the collapsed summit (Flinders et al. 2022). This exercise is an example of using physically based modeling during an ongoing event to supplement monitoring data, as recommended in a 2017 report by the U.S. National Academy of Sciences, Engineering, and Medicine.

3.5.3 Monitoring Methods and Strategy

Detection of changes in groundwater pressure, chemistry, and temperature requires systematic measurements in either continuous or survey mode. Most continuous, long-term hydrologic

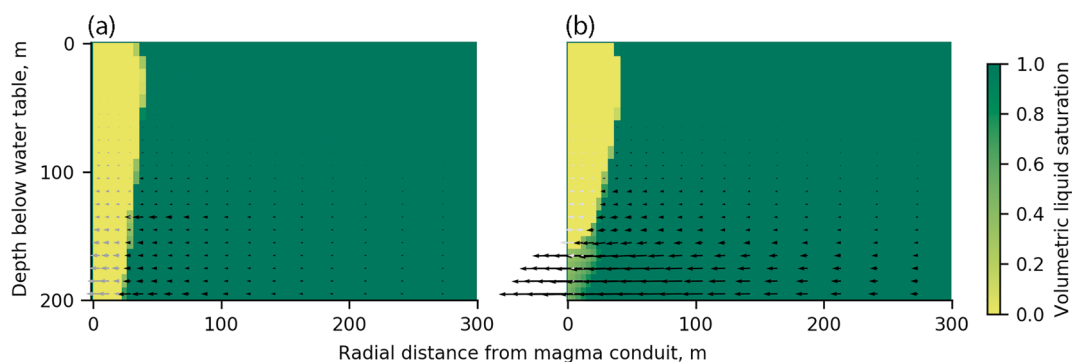


Fig. 19 Liquid water saturation and flow vectors for liquid (green) and steam (yellow) in host rock with horizontal permeability $k_x = 10^{-14}\ \text{m}^2$ and $k_x/k_z = 100$ **a** 1 year and **b** 3 years after drainage of a short-lived (10 years) and narrow (50 m radius) magma conduit. The enhanced

flow at greater depths reflects the greater driving force for fluid flow after the inner boundary condition changes (after magma drainage, pressure along the inner boundary is held at 0.1 MPa). After Ingebritsen et al. (2021)

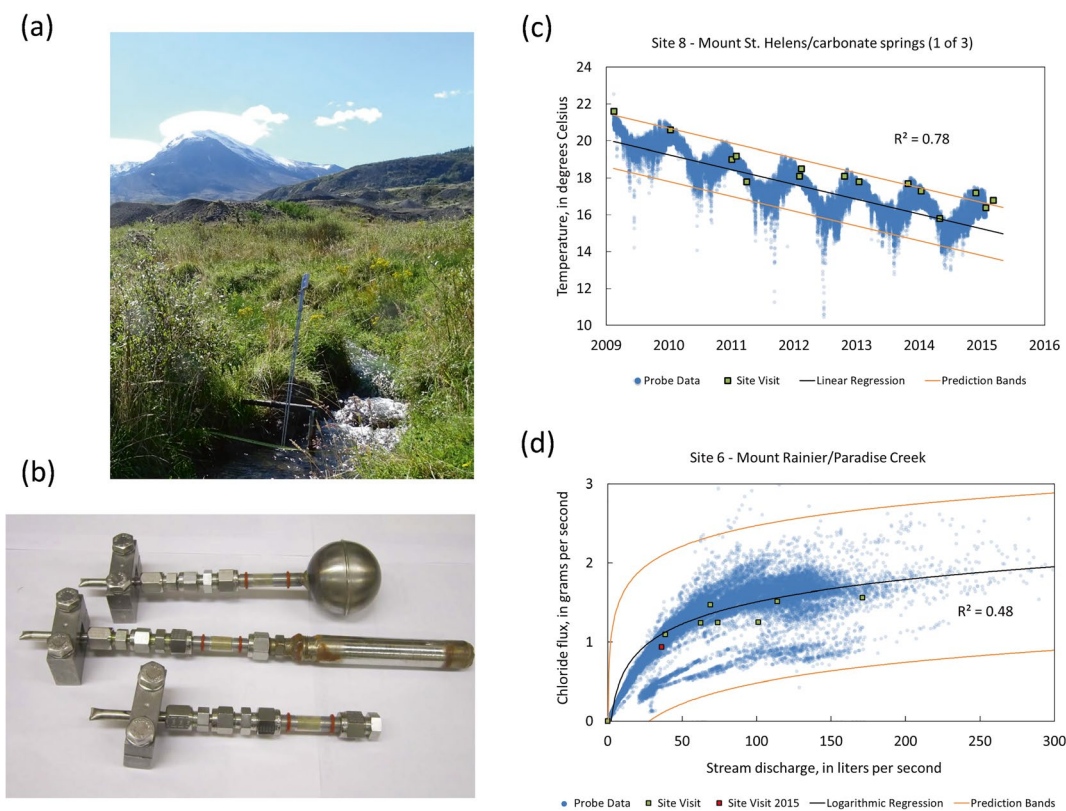


Fig. 20 **a** Pressure–temperature–electrical conductivity (P-T-C) sensor installed at Mount St. Helens (COTS technology); **b** suite of passive-diffusion samplers with varying equilibration times (research technology from University of Utah Noble Gas Laboratory); **c** 7-year

temperature record from P-T-C sensor at the Mount St. Helens site; and **d** 5-year relation between chloride flux and stream discharge at a site below Paradise Warm Springs on Mount Rainier. **c** and **d** from Crankshaw et al. (2018)

monitoring to date has emphasized a subset of relatively easy-to-measure parameters, namely fluid pressure, temperature, and electrical conductivity. Commercial off the shelf (COTS) instrumentation includes devices that can measure pressure, temperature, and electrical conductivity (P-T-C) within a spring, stream, lake, or well (Fig. 19a). These devices typically contain a memory cache that can store several years of data collected at hourly intervals. When needed, such data can be telemetered in real time. Site conditions on volcanoes commonly pose severe challenges for continuous sensors, including high-temperature and corrosive waters and energetic and (or) sediment-laden streams. However,

sensor technology and reliability continue to improve.

Ion-specific probe technology may make it possible to directly sense and quantify concentrations of species of interest such as dissolved inorganic carbon, chloride, sulfate, boron, arsenic, and mercury, but can suffer from sensor stability problems (e.g., drift). Another persistent challenge is latency with respect to lab-based geochemical measurement of key constituents such as He-isotope ratios. This issue has motivated a number of experiments. For instance, a passive-diffusion-sampler suite (Fig. 19b) was tested as a method of deconvolving the time history of He concentration and $^3\text{He}/^4\text{He}$ ratio

in springs and fumarolic areas at several U.S. volcanoes (Dame et al. 2015) and in Japan. In other attempts to track time history and decrease latency, compact and low-power mass spectrometers have been tested (Bajo et al. 2012; McMurtry et al. 2019). Neither the passive-diffusion-sampler suite nor the compact mass spectrometers are ready for operational deployment; they remain experimental. Such experimentation is complemented by ongoing sensor developments aimed at other remote environments, such as seafloor hydrothermal systems and planetary or lunar bodies.

Another useful instrument for background or long-term studies is an autosampler that pumps water into a series of sample containers at a set interval (hourly, daily, weekly) for later manual retrieval and laboratory analysis of a time series. Such automation can greatly enhance the efficiency of baseline investigations to understand hydrothermal dynamics, but still requires human attendance and sufficiently robust equipment. Long-term osmotically pumped fluid samplers have been used to autonomously collect continuous small-volume water samples in remote subsurface environments for up to several years (Jannasch et al. 2004).

Long (multiyear) and high-resolution (hourly or better) hydrologic time series are ideal for determining whether hydrologic anomalies are related to volcanic unrest, to residual effects of previous intrusions or eruptions, or to nonvolcanic phenomena. Nonvolcanic forcings include seasonality and secular trends (Fig. 20c), changes in meteoric-water flux (Fig. 20d), tectonic earthquakes, and anthropogenic influences. These nonvolcanic forcings typically cause sufficient variability in hydrothermal behavior that, in the absence of baseline data, one-time measurements during unrest may have limited interpretive value.

It is often useful to convert the pressure (water level) data from P-T-C probes (Fig. 20a) to a water mass flux, by employing stream-gauging techniques. The water mass flux can then be converted to a heat flux (using the T values) and the mass flux of ionic species of interest (using C values: Fig. 20d), provided that there

are sufficient calibration data (McCleskey et al. 2012). At the Yellowstone Caldera, long-term monitoring of river solutes has allowed calculation of the chloride flux, a proxy for heat discharge from the subsurface magma (Hurwitz and Lowenstern 2008; McCleskey et al. 2016). This is readily accomplished at Yellowstone because of the presence of established stream-gages (<http://waterdata.usgs.gov/usa/nwis/>).

Similar studies on stratocones (cf. Berlo et al. 2020) or shield volcanoes would be scientifically useful, but are logistically challenging, potentially requiring streamgages on numerous drainages, complemented by either frequent manual sampling or deployments of equipment to measure water temperature and chemistry. Another challenge is that some volcanic areas, especially shield volcanoes, are characterized by porous rocks and soils, such that surface streams are rare and replaced by distant, dilute large-volume springs with only a trace of volcanically sourced water (Manga 2001). A recent effort to establish baseline conditions in these more-challenging environments involved 25 sites at 10 of the high-threat volcanoes in the U.S. portion of the Cascade Range. The Cascades network involved 32 sampling points, with up to 45 hourly-recording instruments in place. Fumarole, spring, stream, and well sites were selected based on indications of ongoing magmatic influence, such as elevated $^3\text{He}/^4\text{He}$ ratios, large fluxes of magmatic CO_2 , and/or large heat fluxes. Multiyear (3–7 yr) records allowed quantitative assessment of seasonal, diurnal, barometric, and tidal variability (Crankshaw et al. 2018). The archived results are expected to provide a robust baseline for comparison during future unrest.

4 Present Challenges and Future Directions

Instrumental volcanic gas monitoring has progressed significantly over the last decade, and the utility of fluid geochemistry for potentially predicting volcano behavior is today indisputably recognized. However, much remains to be

done to exploit the message delivered by volcanic gases even more successfully.

Volcanic gas monitoring networks remain technologically immature, and hence less robust, than geophysical instrumentation. The Multi-GAS technique has represented a real breakthrough in volcanology, but challenges remain in long-term maintenance in the harsh volcanic crater environment. Further, the number of gas species that can be detected is still relatively small, although progress is being made and implementations are underway (Roberts et al. 2017; Salas-Navarro 2022). It is expected that progress in miniaturized sensor technology in the next decade(s) will revolutionize the way we monitor volcanic gas composition in real time. Flying sensor-carrying drones into volcanic gas plumes is feasible today (Liu et al. 2020) but still a frontier topic (James et al. 2020). It is foreseeable that fully autonomous drones, with even smarter operability and higher payload, will become standard tools for volcanic gas monitoring. Unmanned Aerial Systems (UAS) will also be increasingly used to collect plume samples, and therefore extend the growing field of plume isotope observations (D'Arcy et al. 2022).

To more quantitatively interpret volcanic gas signals, there is urgent need to better link the volcanic gas community with experimentalists, modelers, and physical volcanologists. Models of volcanic degassing are constantly improving (Iacovino et al. 2021; Wieser et al. 2022) as new volatile saturation models become available (Papale et al. 2022), fueled by progress in solubility/volatile partitioning experiments (Baker and Alletti 2012; Ding et al. 2023). With improved models, the magma source region depths that feed gas emissions at open-conduit volcanoes may be revisited; they may ultimately be deeper than thought today (Ding et al. 2023). Magma fluid-dynamics and gas geochemistry must be better tied if we are to fully understand the mechanisms of separate gas bubble ascent from deeply stored magmas, as this process is likely to be central in explaining the observed gas 'precursors'. Ultimately, to become a full partner in effective forecasting, work is required

to improve methods of real-time volcanic gas signal processing and visualization, and to adopt artificial intelligence tools for automatic pattern recognition and anomaly detection.

Soil diffuse-degassing science has not experienced major technical improvements in the last two decades. Especially regarding CO₂ emissions, the methods used today are similar to those implemented at the beginning of this century. Research has shown the need for spatial measurements over a dense sampling grid, which may be quite time-consuming. Due to practical constraints (topography, permits), a regular grid may be difficult to obtain. Eddy covariance, under appropriate atmospheric and terrain conditions, may contribute to monitoring fluxes over a wider area (Werner et al. 2000; Lewicki and Hilley 2009; Lewicki et al. 2008; Lewicki 2021), even if accumulation chamber methods are preferred to produce high resolution maps (Lewicki et al. 2012). This methodology has been mainly applied in the USA, at Yellowstone (Werner et al. 2000) and Mammoth Mountain (Lewicki et al. 2008; 2012; Lewicki 2021), though Werner et al. (2003) also showed its ability to monitor fluxes at Solfatara (Italy). Additional studies combining accumulation chamber and eddy covariance techniques in degassing areas with more complex topography and weather conditions would be useful. Application of remote sensors to map diffuse degassing areas, for instance using drone technology, could contribute to overcoming difficulties to some extent, but the high atmospheric CO₂ concentrations will remain a challenge. Low-cost portable instruments to detect carbon isotopes in the field would also be welcome, since they could help to understand gas sources in real-time. The development of portable sensors to accurately measure noble gases released from soils would also be a major contribution to better understanding and studying diffuse degassing.

Automatic, permanent CO₂ stations are still quite expensive, especially as additional environmental parameters are required to filter the CO₂ time series. Novel low-cost, easily deployable sensors are urgently needed to widen the

range of application of soil degassing, especially in developing countries. Permanent networks are very scarce relative to the universe of potentially active volcanic systems.

Hydrologic-monitoring strategies are still evolving. A generic standard has yet to be defined and agreed upon. This reflects still-sparse databases, evolving technology, and the fact that the relation between geochemical and thermal anomalies in water and volcanic unrest may be difficult to assess without volcano-specific conceptual models and sufficient baseline data. Potential hydrologic-monitoring sites at various volcanoes range from rare and hard-to-access to very abundant, and research at localities such as Three Sisters has shown that not all springs and streams on a volcano will respond to unrest. This makes it difficult to determine in advance the optimal placement of monitoring sites. Further, safety factors can complicate rapid response during unrest, limiting where samples can be obtained and new instrumentation installed.

An ongoing planning effort for hydrologic monitoring at active volcanoes in the United States envisions the following series of priorities: (1) For lower-risk volcanoes, compile an inventory of fumarole, spring, stream, and well sites with indications of ongoing magmatic influence such as elevated $^3\text{He}/^4\text{He}$ ratios, large fluxes of magmatic CO_2 , and/or large heat fluxes. Where such sites exist and are reasonably accessible, sample and measure every 5 to 10 years to gradually define baseline conditions and develop 'rating curves' to infer parameters of interest (e.g. water flux, heat flux, ionic concentrations) from more readily measured parameters (e.g. water level, temperature, electrical conductance). (2) For moderate-risk volcanoes, where appropriate sites exist, sample and measure every 3 to 5 years to gradually define baseline conditions and develop rating curves. (3) For high-risk volcanoes, where appropriate sites exist, install instrumentation and maintain multiyear (3–5 year) hourly (or better) records of parameters such as fluxes of heat and

magmatically derived solutes, allowing quantitative assessment of variability due to factors such as tectonic earthquakes and seasonal, diurnal, barometric, and tidal influences. All of these efforts will need to be prioritized based on relative threat level, exposed population, logistical complexity, cost, and other factors such as evolving technology. Enhanced hydrologic monitoring should be accompanied by quantitative modeling of hydrothermal behavior, which provides a basis for closing observational gaps and can thereby improve forecasting (National Academy of Sciences 2017).

Our review here shows that geochemical monitoring of volcanic fluid is, and will remain, a multidisciplinary matter: there is no single observational method or signal that can universally be applied to all volcano settings/conditions. Geochemical monitoring strategies need to be readapted and implemented as volcanoes become increasingly restless. During long-lived dormancy of closed-conduit volcanoes, volcanic gas monitoring needs to primarily rely on regular direct sampling campaign of fluids (fumaroles, crater lakes, diffuse degassing, groundwaters). As volcanic unrest starts, however, instrumental observations become increasingly important, requiring the implementation of gas sensing permanent installations (e.g., Multi-GAS, accumulation chambers). As unrest intensifies while eruption becomes more imminent, remote sensing techniques (e.g., ground-based scanning UV spectrometers, Fourier Transform InfraRed spectroscopy, satellite-based spectroscopy) become the key tools of the trade (Kern et al. 2022; Campion et al. this book).

Acknowledgements The authors wish to thank Bill Evans, Maarten de Moor and Eleazar Padrón for insightful reviews. A.A. received funding from the Italian Ministero Università Ricerca (MUR, Projects PRIN2017LMNLAW and PRIN2022HA8XCS), and from the RETURN Extended Partnership funded by the European Union Next-Generation EU (National Recovery and Resilience Plan–NRRP, Mission 4, Component 2, Investment 1.3–D.D.1243 2/8/2022, PE0000005).

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Remote Monitoring of Volcanic Gases

Robin Campion 

Abstract

Volcanic degassing drives eruptions and influences Earth's atmospheric composition and climate over geological timescales. Measuring the emission rates of the key magmatic gases emitted through passive degassing and eruptions is crucial for volcano monitoring, and remote sensing techniques plays an absolutely central role in this task. This chapter reviews the principles, techniques, and applications of remote sensing for volcanic gas monitoring, focusing on four key methods: 1. Differential Optical Absorption Spectroscopy (DOAS)—Measures SO_2 and some halogen oxides (BrO , OCIO) via Ultraviolet spectroscopy, enabling flux calculations either through mobile measurements or fixed scanning instruments, as implemented the NOVAC network. I present the formulas used to calculate SO_2 flux for each measurement set-up, and discuss their respective merits and limitations, concluding that mobile measurements provide a better accuracy while scanning measurements offer a higher time resolution and automation. 2. SO_2 Cameras—Provide

high-temporal-resolution flux measurements and 2D images of SO_2 in the plume. The lack of highly-resolved spectral information and viewing geometry inherent to this methods results in the need of corrections for light dilution and aerosol interference. Several satisfying options exist for the former, much less for the latter. 3. Open-Path Fourier Transform Infrared (OP-FTIR) Spectroscopy—Measures multiple gases (SO_2 , HCl , HF , H_2O , CO_2 , SiF_4) in infrared atmospheric windows. The three most common instrumental set-up are reviewed and discussed: solar occultation, short-path, and thermal emission each one being suited to different volcanic settings, wavelength ranges and gas species. 4. Satellite Remote Sensing—Tracks global SO_2 emissions using UV (e.g., TROPOMI) and IR sensors (e.g., IASI), though retrievals depend on plume altitude and atmospheric conditions. Satellite remote sensing still lacks the sensitivity of ground-based methods but usually gives more accurate results for very large emissions. Recent advances in sensors and algorithms has allowed measuring other more volcanic gases than just SO_2 . Then, I briefly

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discuss the processes that control the gas composition (geodynamic context, magma source depth, degree of previous degassing and hydrothermal interactions) and SO_2 flux (change in magma supply, bubble migrations, outgassing, conduit sealing and hydrothermal scrubbing). Finally I review recent advancements in the field, such as hyperspectral gas imaging, Fabry-Perot based UV cameras, and geostationary satellites (e.g., TEMPO) for real-time monitoring, and expose its current challenges, such as retrievals of gas in ash-laden plumes and correcting for radiative transfer complexities.

Volcanic degassing is the eruptions driving force, and exerts, over geological times, a crucial regulating effect on the atmospheric composition and climate on Earth (e.g., Ryan McKenzie et al. 2016, Stordal et al. 2017). After a short introduction on the origin and nature of volcanic gases, we briefly revisit the historical development of volcanic gas remote sensing, and we describe with more detail four techniques, with their different implementations, which are the most widely used for volcano monitoring: Differential Optical Absorption Spectroscopy (DOAS), SO_2 cameras, Open Path Fourier Transform Infrared spectrometry (OP-FTIR), and satellite measurements. Finally, we provide some guidelines to interpret the data and discuss the potential volcanic processes that control the variations of gas flux and composition measured by remote sensing.

1 Volatiles in the Magma

The Earth's mantle contains a small but significant amount of volatiles, a term that defines compounds that are under liquid or gaseous state in the conditions of pressure, temperature and redox potential prevailing at the Earth's Surface, and that includes water, carbon, sulfur and halogens species, and noble gases. Part of them have been trapped since the accretion of the Earth, while the other part is derived from the hydrated

and carbonated oceanic crust and sediments that dive in the subduction zones (e.g. Fischer and Marty 2005; Churikova et al. 2007). This recycling mechanism of volatiles explains why subduction zone magmas are generally richer in volatiles than oceanic ridge magmas (e.g. Giggenbach 1996). The relative abundances of volatiles in the mantle, although not known precisely, must thus be highly heterogeneous. During the partial melting of the mantle that leads to magma generation, volatiles partition heavily into the melt phase. In subduction zones, the release of volatiles by the dehydration of the subducted slab is even the fundamental cause for magma generation, by lowering the solidus of the overlying mantle wedge.

The amount of volatiles dissolved in primitive magmas is usually estimated from microprobe analysis of the melt inclusions trapped inside crystals that formed in the magma chamber (e.g. Spiliaerts et al. 2006; Metrich and Wallace 2008). Only early-formed minerals (i.e. highest Mg# olivines or highest An. plagioclases) should be considered to avoid volatile depletion associated with early magma degassing. Yet, numerous evidence from experimental petrology (e.g. Scaillet and Pichavent 2003) and budgets between degassed and erupted magma (e.g. Wallace 2001) indicate that the volatiles in the primitive magmas are either underestimated (e.g. Zelensky et al. 2022) or present as a separated fluid phase coexisting with the silicate melt in the magma chamber, and even as early as in the upper mantle (e.g. Allard 2010). This fluid phase could amount to 1 weight % of the total magma in subduction zones volcanoes and is significantly enriched in carbon and sulfur compared to the composition of volatiles dissolved in the silicate melt (Scaillet and Pichavent 2003).

When reaching saturation, volatile elements exsolve from the magma and escape into the atmosphere as gaseous compounds. Hydrogen is present very predominantly as H_2O , with minor amounts of H_2 (e.g. Kazahaya et al. 2022). Water vapor is nearly always the most abundant volcanic gas. CO_2 , usually the second most abundant volcanic gas, is the predominant

Carbon compound and CO is present only in small amounts in high-temperature gases (e.g. Giggenbach 1987; Kazahaya et al. 2022). SO₂ is the predominant Sulfur compound in high-temperature (>500 °C) magmatic gases, but, in lower temperature gases that have interacted with hydrothermal systems, H₂S is often predominant (e.g. Symonds et al. 2001). Halogen compounds are dominantly present as HCl, HF, and HBr (e.g. Aiuppa et al. 2009), although traces of SiF₄, a product of an equilibrium reaction between HF and silicate glasses, is also found in minor quantities (e.g. de Hoog et al. 2005).

2 Remote Sensing of Volcanic Gases: General Considerations and Historical Development

Volcanic Gasses were first studied by chemists of the 18th and early nineteenth centuries, but repeatable, meaningful results were only obtained in the twentieth century, after several methodological issues in sampling, and analytics had been solved. Due to the often difficult and sometimes dangerous nature of the direct sampling operations, volcanologists have adapted a wide range of methodologies to measure the composition of the volcanic gases from a distance, by measuring the electromagnetic radiation passing through or emitted by them. Figure 1 gives an overview of the most used methods, organized by wavelength range (Infrared versus Ultraviolet), platform type (space- or ground-based), and spectral resolution. This figure serves as a guiding thread for this chapter, and the most used methods are discussed in the following paragraphs.

But before describing them, to ensure that the readers get a good understanding on how they work, it is important to briefly define the basic concepts and laws of how radiation propagates in the atmosphere. They are presented in this chapter in a very synthetized and simplified way, with an emphasis on the remote sensing methods presented later in this chapter. Among

the numerous books available on that topic, the reader wanting a more detailed information can consult Andrews (2002), Liou (2002) or Ulrich Platt and Stutz (2008).

The radiation that is emitted by matter at a temperature T follows a spectral distribution described by Planck's law, annotated $B_\lambda(T)$ and illustrated in Fig. 2a.

$$I = \varepsilon(\lambda) \cdot \frac{2hc^2}{\lambda^5 (\exp((hc/\lambda kT) - 1))} \quad (1)$$

where λ is the wavelength, h is the Planck's constant ($h=6.626 \cdot 10^{-34}$ J.s, and c is the speed of light ($c=2.9979 \cdot 10^8$ m/s), k is the Boltzmann's constant $k=1.38065 \cdot 10^{-23}$ J/K and ε is the emissivity.

When radiation propagates into a homogeneous gas layer with a thickness z , which contains n different gas species with concentrations C_i , its intensity is absorbed by the gas molecules to produce transitions to higher energy quantum states, which are ultimately dissipated as an increase in gas temperature. This absorption is described by the Bouguer-Beer-Lambert's law (Fig. 2b), which can be written as

$$I(\lambda) = I_0(\lambda) \cdot e^{-\sum_i \sigma_i(\lambda) \cdot C_i \cdot z} \quad (2)$$

where $\sigma_i(\lambda)$ (expressed in cm²/molecule) is the absorption cross-section of gas species i , which is specific to-, and characteristic of it. Additionally, $\sigma_i(\lambda)$ also varies with temperature and pressure, especially in the Infrared and Microwave region (temperature and pressure broadening). In atmospheric remote sensing, unlike in laboratory, z is usually not known, so that the quantity that is retrieved is the product of concentration and thickness, which is called the column density. The product $\sum_i \sigma_i(\lambda) \cdot C_i \cdot z$ is called the optical thickness.

This same layer of gas will also emit radiation (Fig. 2b) that follows the law:

$$I(\lambda) = B_\lambda(T) \cdot \left(1 - e^{-\sum_i \sigma_i(\lambda) \cdot C_i \cdot z}\right) \quad (3)$$

where $B_\lambda(T)$ is Planck's function at the gas temperature T .

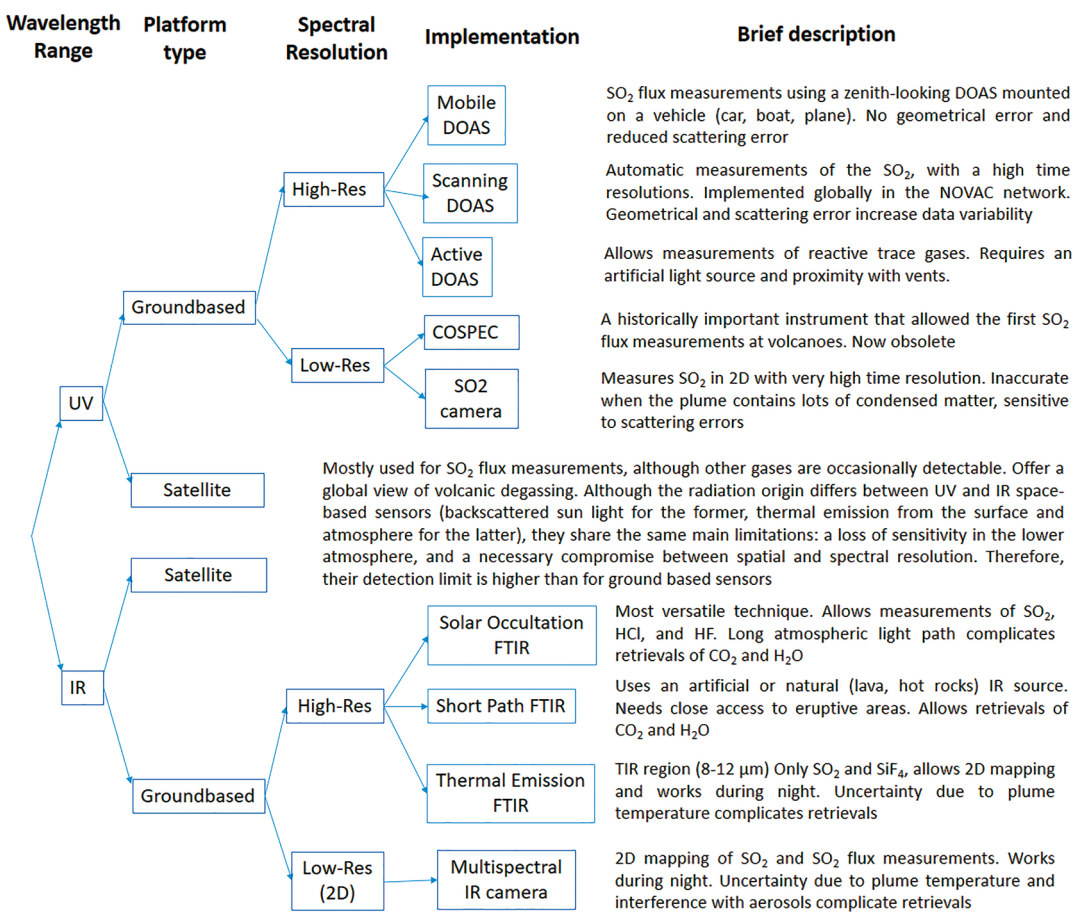


Fig. 1 Classification of volcanic gas remote sensing techniques, based on spectral range, platform type, and spectral resolution, with a brief summary of each of them

Apart from emission and absorption, a third process affects significantly the propagation of the radiation in the atmosphere: scattering. Scattering is the redistribution of the radiation away from its propagation direction due to its interaction with heterogeneities of its propagation medium. The radiation intensity is attenuated in the propagation direction, while it is increased in the other directions. In the atmosphere, heterogeneities range in size from molecules (~10⁻¹⁰m) to water droplets (10⁻²m), which don't scatter light in the same way. Three types of light scattering can be distinguished: Rayleigh and Raman scattering occurs due to molecules. The former is an elastic scattering

whose efficiency is proportional to λ^{-4} . The latter is an inelastic scattering. Mie scattering, is a combination of refraction and absorption of light caused by particles whose mathematical treatment is complex in details. Its scattering efficiency has a wavelength dependence of $\sim \lambda^{-1}$ to $\lambda^{-1.5}$ and a strong spatial anisotropy.

Contrary to direct measurements, remote measurements yield path-integrated concentrations called column densities. This fundamental difference has made the validation of remote measurements with direct measurements difficult, especially because the volcanic plumes are highly heterogeneous. Column densities are expressed in a large number of units, among

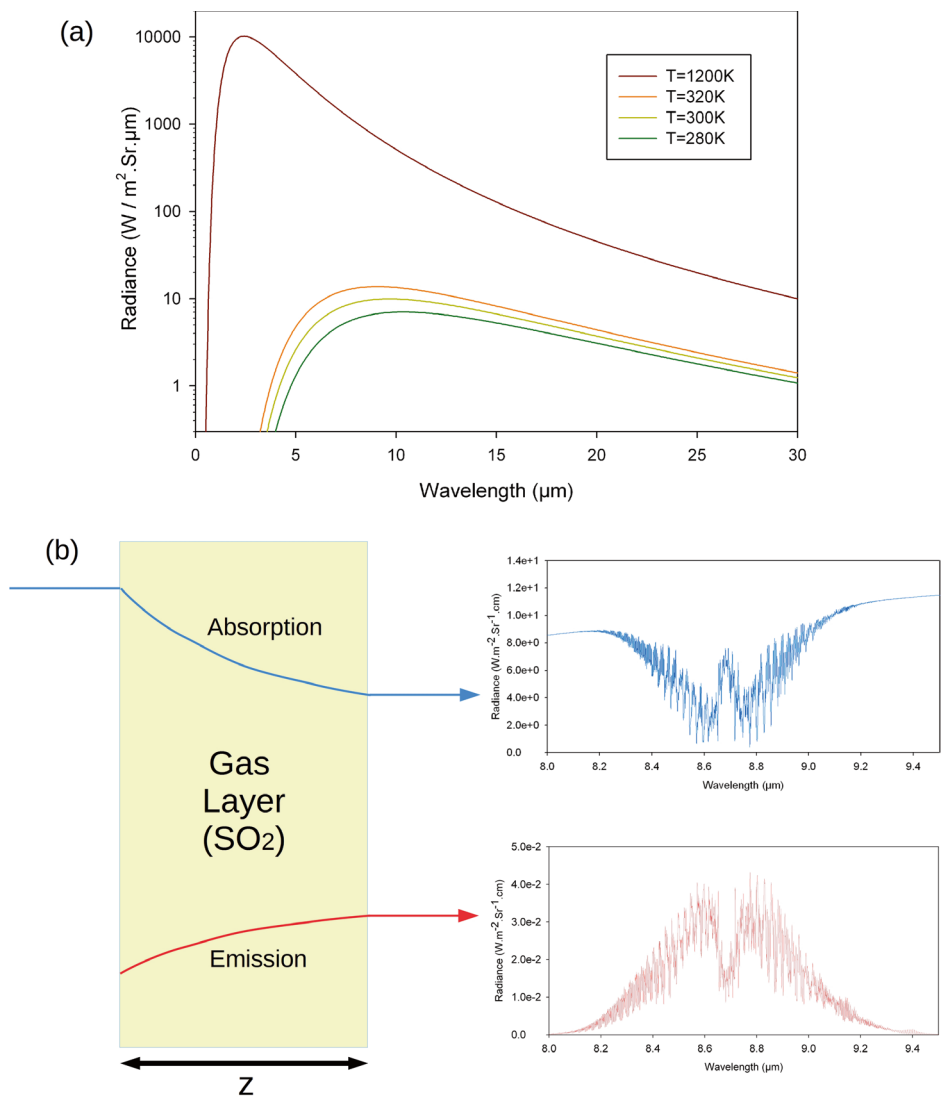


Fig. 2 **a** Spectra, in logarithmic scale, of thermally emitted radiation (Planck’s curve) for blackbodies of atmospheric and magmatic temperatures. Note how the bodies at atmospheric temperature do not emit significant

thermal radiation below $4 \mu\text{m}$. **b** Spectral distribution of the infrared radiation transmitted (blue curve) and emitted (red curve) by a 200m thick layer of pure air containing $15\text{g}/\text{m}^2$ of SO_2 at 260K

which some are inherited from the earliest era of remote sensing. Since this exotic diversity may sometimes generate confusion, we hereafter provide the following table with conversion factors between the different units used in the literature (Table 1).

The first attempt to remotely measure gas composition dates back, to our knowledge, from the middle of twentieth century, when

Belgian geologist John Verhoogen and astronomer Armand Delsemme successfully obtained night-time emission spectra, in the visible wavelengths, of combustion flame from gas vents in Nyamuragira and Nyiragongo volcanoes (Verhoogen 1948; Delsemme 1960). With exposure times of up to 10 h (!), they could identify the presence of hydrogen, sodium, and copper in the emission lines of the spectra. These

Table 1 Conversion factors for the various units commonly used to measure SO₂ column amounts. Factors are given to convert units at a given line into units at a given column

From/To	g/m ²	Molec/cm ²	ppm.m	DU
g/m ²	1	9.41E+17	3.76E+02	3.50E+01
molec/cm ²	1.06E-18	1	3.99E-16	3.72E-17
ppm.m	2.66E-03	2.50E+15	1	9.32
DU	2.86E-02	2.69E+16	1.07E-01	1

measurements, however, remained somewhat anecdotic and were not subsequently repeated, because the elements that are detectable with this technique are by far not the most abundant among the volcanic gases.

3 Ground-Based Ultraviolet Remote Sensing

3.1 COSPEC or the Beginning of SO₂ Flux Measurements

A significant turning point of remote sensing of volcanic gases came, in the mid-seventies, with the invention of the COSPEC (CORrelation SPECTrometer), an 8-band Ultra Violet grating spectrometer initially designed to measure the SO₂ and NO₂ emissions from power plants (Moffat and Millan 1971). The complex optomechanical design of COSPEC makes it almost insensitive to light intensity changes and spectral interferers like Ozone (Millan 2008). The calibration of the spectrometer is insured by passing two sealed quartz cells, containing known concentrations of SO₂, in the optic beam inside the instrument. The simple operation of the COSPEC, its “black box” philosophy, and its robustness, made it rapidly quite popular among volcanologists. It allowed to quantify, or at least estimate, the emission rates of SO₂ by volcanoes, something that was not possible before. This yielded considerable advances in the understanding of the volcanoes’ dynamics, such as the identification of the excess sulfur problem (e.g. Wallace 2001), the concepts of magmatic convection (e.g. Kazahaya et al. 1994; Stevenson and Blake 1998) or the sealing of volcanic conduits (e.g. Fischer et al. 2002). COSPEC remained the

standard in measuring SO₂ emission rates at volcanoes until the early 2000’s.

3.2 DOAS: Cheaper Lighter and Better

The advent of smaller, lighter, and, importantly, cheaper spectrometers, called Mini-DOAS, marked a significant evolution in the ground-based remote sensing of volcanic gases. Contrary to the COSPEC, which outputs an analog electric signal proportional to the column density of SO₂, the mini-DOAS record full spectra, from which more gases than just SO₂ can eventually be retrieved such as BrO, IO, OCIO (review in Bobrowski et al., 2007). The mini-DOAS spectrometers are composed of an entrance slit, a diffraction grating, and a CCD (Charge Coupled Device) sensor that records the intensity of the diffracted light over its entire length (Fig. 1a).

The optical set-up of the spectrometer, particularly the combination of the entrance slit width and the line density of the grating, defines the wavelength range and spectral resolution of the spectrometer, which are always trading off with its light throughput.

Retrieving SO₂ column densities requires processing the spectra. First, the measured spectra $I(\lambda)$ are divided by a reference spectrum $I_0(\lambda)$, which is obtained outside of the volcanic plume. Then, the Beer-Lambert law (Eq. 2) is adapted so that the absorption cross section is splitted into a broadband component and a narrowband one, which has only the rapid succession of peaks at closely spaced wavelengths, and is called the differential absorption cross section. This adapted form of Beer-Lambert law, written

as Eq. (4), is used to adjust a modeled differential spectrum until it matches as closely as possible the measured one.

$$-\ln\left(\frac{I(\lambda)}{I_0(\lambda)}\right) = \varepsilon_s(\lambda) + \sum_i \sigma_i^B(\lambda) \cdot X_i + \sum_i \sigma_i^N(\lambda) \cdot X_i \quad (4)$$

The slant column density X_i of gases that absorb in the considered spectral region is fitted, whereas a polynomial is fitted to account for both the broadband component of molecular absorption σ_i^B and the aerosol extinction ε_s , which is also broadband. σ_i^N , the differential absorption cross sections, are obtained by applying a low pass filter to $\sigma_i(\lambda)$. The principal gas that absorbs in the wavelength spectral region used to measure SO₂, and needs to be fitted together with it, is ozone. The effect of inelastic Rotational Raman scattering, known as the Ring effect, is treated as a narrowband absorber and is adjusted as a pseudo-slant column.

Practically, when performing a DOAS fit to retrieve SO₂, several points require special attention to be paid in order to obtain accurate results. These are:

- Checking that the residual (i.e. the difference between the measured and modeled spectrum) presents no spectral structures, which may indicate either that an additional gas needs to be included in the fit or that the calibration of the spectrometer is imperfect.
- Checking the calibration of the spectrometer, and eventually recalibrating it. Spectrometer calibration consists of two operations: Establishing the exact correspondence between pixel position in the detector and wavelength, and characterizing the line shape function of the instrument. These two operations are performed by taking the spectra of a mercury lamp, whose atomic emission lines are almost monochromatic and have their wavelength precisely known. Some software, such as Q-DOAS, developed by the Belgian Institute for Spatial Aeronomy (Danckaert et al. 2014), can correct small changes in spectrometer calibration based on the position and width of the Fraunhofer lines of the solar spectrum.

- Choosing the spectral window for retrievals. Windows starting at a short wavelength typically produce less noisy retrievals, because SO₂ absorption gets stronger toward shorter wavelength, but are more affected by stray light and the light dilution effect (Mori et al. 2006; Kern et al. 2010a, b, 2012), especially for concentrated plumes. For volcanic plumes that are not too concentrated or too distant from the spectrometer, a window ranging from 312 to 325 nm is a good compromise between precision and accuracy. Otherwise, a reasonably simple approach to improve, at first order, the accuracy of the retrievals, is to use adaptive spectral windows (Fickel and Granados 2017), with longer wavelength fitting windows (360–390 nm) giving much more accurate results in case of extreme SO₂ column densities (Bobrowski et al. 2010).

The DOAS technique is particularly suited for measuring the SO₂ flux (e.g. Galle et al. 2003), but it has also allowed to detect and measure halogen oxides, such as BrO (Bobrowski et al., 2003) and OCIO (Bobrowski et al. 2007), which are produced by the photocatalytic oxidation of primary magmatic HBr and HCl.

3.3 Calculating SO₂ Emission Rates with DOAS

There are essentially two ways to operate a DOAS spectrometer in the field for SO₂ flux measurements, and they are essentially the same as for COSPEC.

The first approach, known as mobile flux measurements or traverse measurements, consists of crossing under the plume with the spectrometer pointing vertically (Fig. 3b), and recording, for each position of the trajectory, the vertical column density (VCD) of SO₂. The SO₂ flux is then simply calculated (Williams-Jones et al. 2008) as

$$F = v \cdot \sum_i (C_i + C_{i+1}) / 2 \cdot \sin(\omega - \theta_i) \cdot l_i \quad (5)$$

where v is the wind velocity, C_i is the VCD measured on position i of the trajectory, ω is the wind direction, θ_i is the azimuth angle of the trajectory at position i , and l_i is the distance between positions i and $i+1$. Car, boat, plane, helicopter, motorcycle, walking, or more recently Unmanned Aerial Vehicle (drone) traverses have been used, depending on plume dimensions, budget, accessibility, and the road network around the volcano. The mobile flux measurements are arguably the most accurate method of measuring SO_2 flux on volcanoes because it is less subject to geometrical and scattering errors than the scanning method, which is detailed next.

The second approach, known as scanning measurements, consists of measuring the slant column density of SO_2 using a fixed instrument in successive directions within a scanning plane (Fig. 3d). In this approach, the flux calculation is more complicated because the length of the segments separating two successive measurements of the scan has to be calculated, and this calculation depends on the geometry of the plume and scanning plane. If the width of the plume is small compared to the distance D between the plume and the sensor, the following approximation, known as radial integration (Williams-Jones et al. 2008), can be used

$$F = v \cdot |\sin(\omega - \theta)| \cdot \sum_i \frac{X_i + X_{i+1}}{2} \cdot D \cdot |\alpha_i - \alpha_{i+1}| \quad (6)$$

where v is the wind velocity, X_i is the slant column density measured at angle α_i of the scan plane measured from zenith, θ is the azimuth of the scanning plane, D is the distance between the plume and the sensor, and α_i is the i th angle of the scan, measured in radians from zenith. For a spectrometer scanning vertically through a horizontal plume D is equal to the plume height (H_p) divided by $\sin(\alpha_i)$.

For wide plumes, or low plumes, the radial integration approximation becomes geometrically too inaccurate and leads to large errors. In those cases, the tangential approximation has to be preferred (Williams-Jones et al. 2008), in which the flux is calculated as

$$F = v \cdot |\sin(\omega - \theta)| \cdot H_p \cdot \sum_i |\tan(\alpha_i) - \tan(\alpha_{i+1})| \cdot \frac{X_i \cdot \cos(\alpha_i) + X_{i+1} \cdot \cos(\alpha_{i+1})}{2} \quad (7)$$

Scanning measurements have a higher error than mobile measurements for two reasons:

- (1) The calculation of the flux depends on the distance between the plume and the spectrometer. The relative error on the flux will be proportional to $\Delta H_p / H_p$, which means that measurements become increasingly imprecise for low plumes. The plume height parameter can be better constrained if the plume is measured simultaneously by two spectrometers in different locations across the plume (Edmonds et al. 2003; Johansson et al. 2009).
- (2) The measurements are more affected by the “Light Dilution” effect (e.g. Mori et al. 2006; Kern et al. 2010a, b) which is caused by photons scattered in the field of view of the spectrometer, which have not crossed the plume. The light dilution effect causes a systematic underestimation of the column density measurements that is proportional to the distance between the instrument and the plume and to the actual SO_2 Column density in the plume. It is also stronger at shorter wavelengths.

3.4 The NOVAC Network

In 2004, a worldwide initiative, funded by the European Union, and coordinated by the Universities of Chalmers and Heidelberg, took DOAS measurements of volcanic SO_2 fluxes at a whole new level: The NOVAC network (Network for Observation of Volcanic and Atmospheric Change, Galle et al. 2010, Arellano et al. 2021). The NOVAC network installed scanning spectrometers on an incremental number of volcanoes in the world (39 as of 2021), to measure permanently (during daylight) and automatically their SO_2 flux. Automatizing the spectra acquisition under the challenging climatic and volcanic environment required the

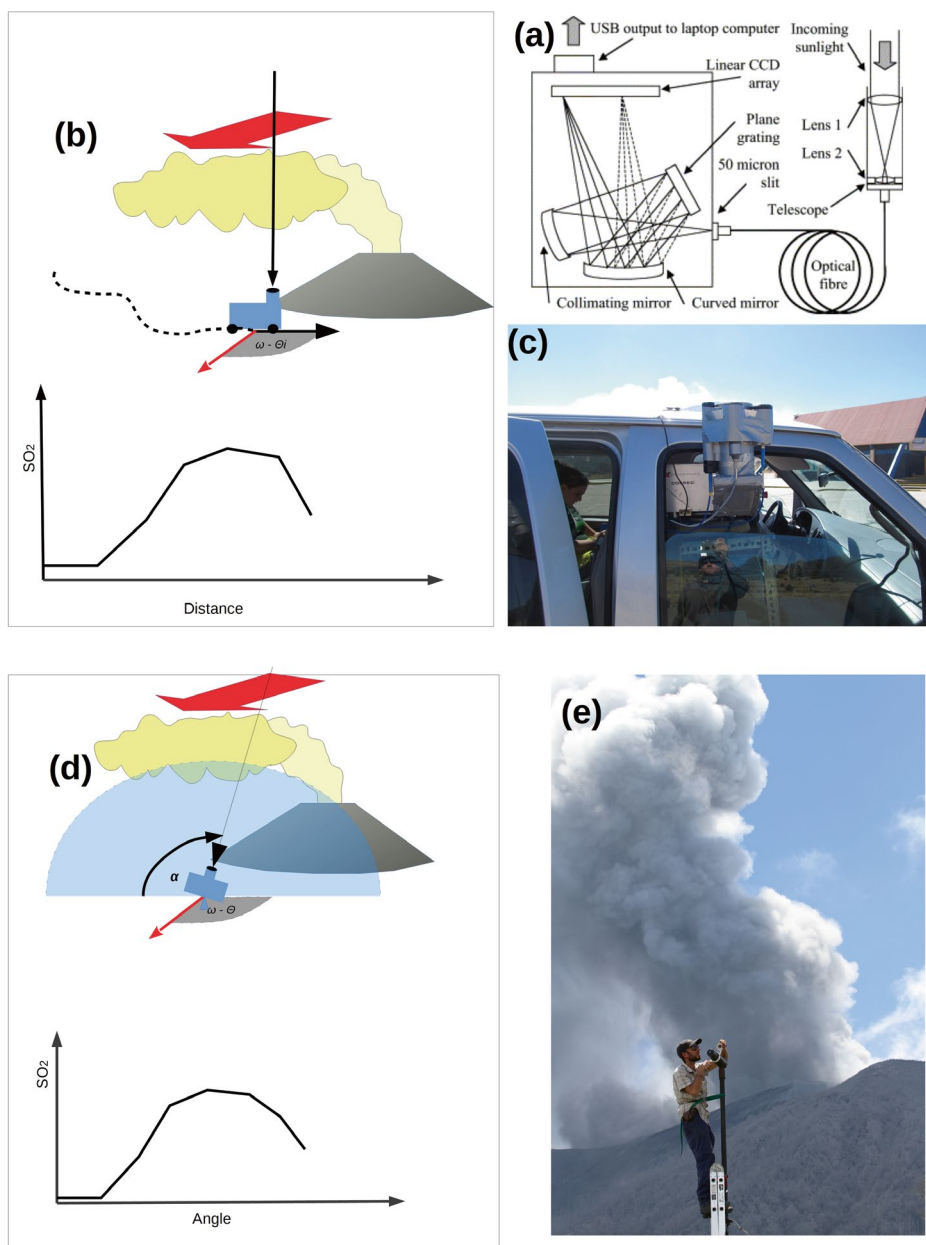


Fig. 3 **a** Internal sketch of a DOAS (Galle et al. 2003, requires permission from Elsevier) **b** Mobile measurements of SO₂ flux using a mobile upwards-looking DOAS. **c** Field set-up of three telescopes mounted together with a COSPEC in the vehicle near Popocatepetl (photo Courtesy M. Fickel). **d**

Measurements of SO₂ flux using a fixed scanning DOAS. **e** On the flank of Turrialba volcano, Maarten de Moor performs maintenance on a scanning DOAS station belonging to the NOVAC network. Animated versions of Fig. 3b and 3d are available as supplementary material

development of a ruggedized scanning and spectra acquisition instrument. The NOVAC instruments contain a motor, coaxial to the optical fibre, which rotates a mirror that is tilted, so that the scanning of the sky is performed in a conical geometry (Fig. 4). Conical scanning was preferred to flat scanning because it provides better coverage of the possible plume directions with a given number of stations. As a result, the geometrical formula for calculating the SO₂ flux from a set of scanning measurements resulted significantly more complex (Johansson 2009) and is given below.

$$F = v \cdot \sum_i \sqrt{(x(\alpha_i) - x(\alpha_{i+1}))^2 + (y(\alpha_i) - y(\alpha_{i+1}))^2} \cdot \frac{\frac{X_i}{AMF_i} + \frac{X_{i+1}}{AMF_{i+1}}}{2} \cdot \sin(\omega - \theta_i) \quad (8)$$

x and y are the horizontal coordinates of the intersection between the scanning cone and the gas plume, assumed to be a horizontal plane located at an altitude H_p above the instrument. For a well-levelled instrument scanning over a half cone with an aperture angle β above the horizon these coordinates are given by

$$x(\alpha_i) = \frac{H_p}{\tan(\beta) \cdot \cos(\alpha_i)} \quad (9)$$

and

$$y(\alpha_i) = H_p \cdot \tan(\alpha_i) \quad (10)$$

AMF_i is the geometrical air mass factor used to convert the slant column density measured at scan angle α_i into a vertical column density. It is given by

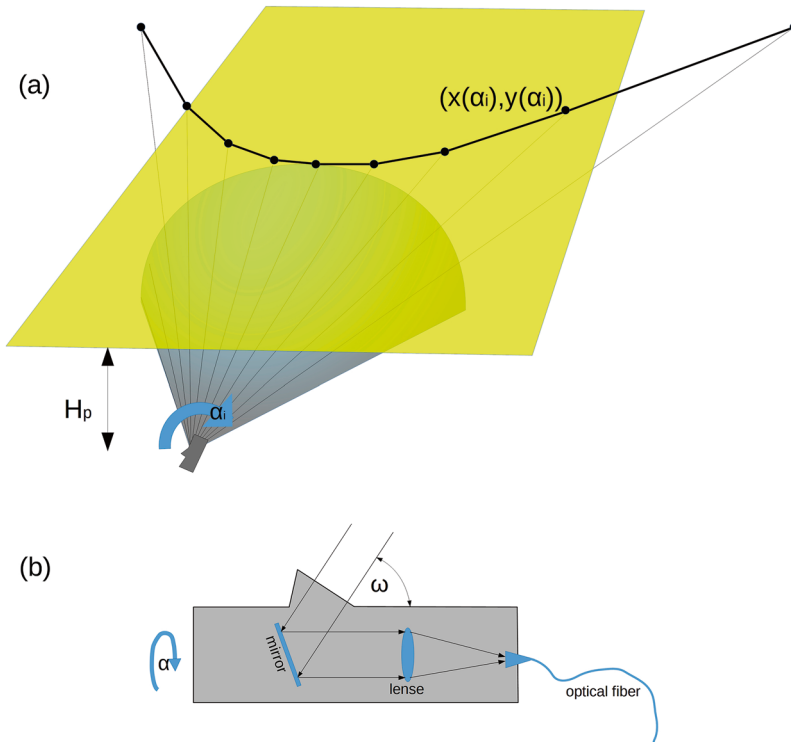


Fig. 4 **a** Conical scanning geometry used by the instruments of the NOVAC network. The geographical positions of the measurements corresponds to the intersection between the scanning cone and a plane located at

the plume altitude. **b** The conical scanning geometry is obtained by rotating coaxially (angle α) the instrument's scanning head, which contains a mirror that is tilted so that it observes the incoming light from a direction ω

$$AMF_i = \sqrt{\frac{1 + \tan^2(\beta) \cdot \sin^2(\alpha_i)}{\tan^2(\beta) \cdot \cos^2(\alpha_i)}} + 1 \quad (11)$$

Finally, similarly to Eq. 5, θ_i is the azimuth angle of the segment connecting points $(x(\alpha_i), y(\alpha_i))$ and $(x(\alpha_{i+1}), y(\alpha_{i+1}))$ and is given by

$$\theta_i = \arctan\left(\frac{y(\alpha_i) - y(\alpha_{i+1})}{x(\alpha_i) - x(\alpha_{i+1})}\right) \quad (12)$$

These formulas may seem complicated, but I believe it is useful to explicit them completely in this chapter because they represent the core of SO_2 flux calculation with the NOVAC instruments, which are so widely spread across the World, and because, as far as I know, they have not been published anywhere but in the Ph.D. thesis of Mattias Johansson (2009).

3.5 SO_2 Cameras

SO_2 cameras are a class of instruments that started being developed in the mid 2000's in order to reduce the uncertainties in flux calculations arising from plume geometry and wind speed, and to increase the time resolution of the measurements (Mori and Burton 2006; Kern et al. 2015). An SO_2 camera typically consists of two UV-sensitive CCD cameras (Fig. 5), which are each equipped with a ~10 nm wide band pass filter. One filter has its maximal transmittance located in the spectral region of the SO_2 absorption in the UV (~310 nm), and the other just outside of it (~330 nm).

The light intensity measured by each camera is actually a spectrally-integrated product

$$I = \int_{\lambda} I(\lambda) \cdot F(\lambda) \cdot Q(\lambda) \cdot d\lambda \quad (13)$$

of $I(\lambda)$, the spectrum of the incident radiation, $F(\lambda)$, the spectral response of the filter and $Q(\lambda)$, the quantum efficiency of the camera sensor. Using a pair of light intensity images recorded by each camera (I_{ij}^{310} and I_{ij}^{330}), the apparent absorbance (Kern et al. 2010b) is calculated on each pixel as

$$\alpha_{ij} = \ln\left(\frac{I_{ij}^{310}}{I_{ij}^{330}}\right) = \ln\left(\frac{I_{ij}^{330}}{I_{ij}^{310}}\right) - \ln\left(\frac{I_0^{330}}{I_0^{310}}\right) \quad (14)$$

where I_0 refers to the sky intensity before it crosses the plume. For the pixels located outside of the plume, $I = I_0$. For the pixels located in the plume, the light intensity is modified by its interaction with SO_2 molecules and aerosols present in the plume, so I_{ij}^{310} and I_{ij}^{330} have to be extrapolated by fitting a function across clear regions. For these plume pixels,

$$I^{310} = I_0^{310} \cdot \exp(-\sigma^* \cdot X) \cdot \varepsilon \quad (15)$$

and

$$I^{330} = I_0^{330} \cdot \varepsilon \quad (16)$$

where σ^* is the band-integrated absorption cross-section of SO_2 and ε is the effect of aerosols present in the plume (ash or liquid aerosols), which scatters and absorb radiation. This can either be a decrease or an increase of the radiation reaching the camera, depending on the geometry of the Sun-plume-camera configuration and on the abundance and single scattering albedo of the aerosol. But since it is a broadband effect and the centroids of the filters are separated by only 20 nm, ε can be approximated as a constant, and Eq. (14) simplifies to

$$\sigma^* \cdot X = \ln\left(\frac{I_{ij}^{330}}{I_{ij}^{310}}\right) - \ln\left(\frac{I_0^{330}}{I_0^{310}}\right) \quad (17)$$

Due to the varying shape of the sky spectrum and the poorly constrained spectral response function of the camera's CCD and of the band-pass filters, σ^* has to be determined empirically, either by passing a set of calibration cells right in front of the camera lenses (e.g. Mori et al. 2006; Dalton et al. 2009) or by comparing with collocated DOAS measurements (e.g. Lübcke et al. 2013).

The sequences of images obtained with SO_2 cameras can be processed with an appropriate algorithm that tracks the motion of the plumes heterogeneities to extract the 2D velocity field of the gas transport in the plume (e.g. Peters et al. 2015), thereby reducing considerably an

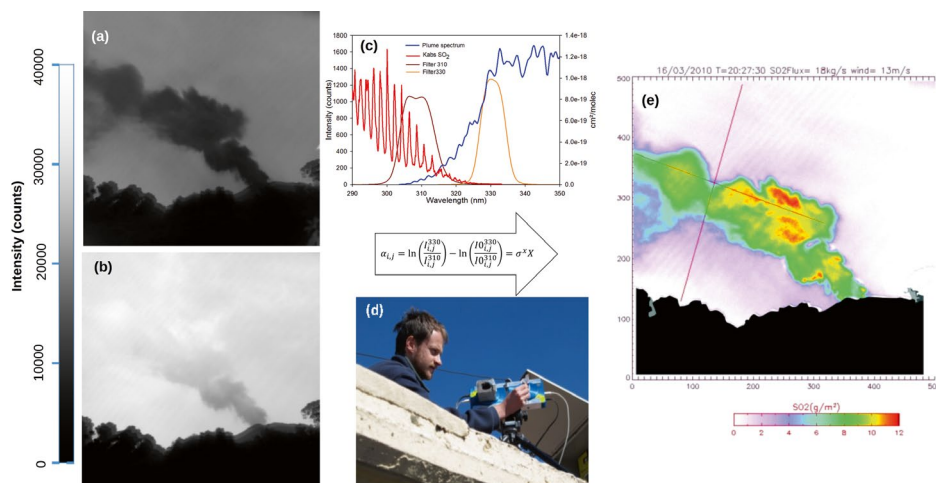


Fig. 5 Processing scheme of UV camera measurements. The camera typically takes two monochromatic images at 310 nm (a) and 330 nm (b). Note the much stronger plume absorption at 310nm (the result of absorption by SO₂ molecules and aerosols) than at 330nm (the result of the aerosol absorption only). (c) Transmittance functions

of both camera filters, plotted together with the absorption cross-section of SO₂ and the spectrum of the diffuse sky radiation. (d) Calibration of the camera with SO₂ cells. (e) 2D-Distribution of the SO₂ in the plume of Turrialba volcano, obtained after processing the image pair shown in (a) and (b)

important source of error on emission rate measurements. Close to the vent, this wind field is always turbulent due to the temperature contrast between the hot gases and the surrounding atmosphere. Moving away a few hundreds to a few thousands of meters, it becomes laminar but may still show some intricate patterns due to the interplay of near-ervent turbulence and wind shear. The SO₂ flux is then calculated, for each image, by defining an integration line around the source and using Eq. 5, treating wind as a 2D vector field.

When measuring in the field with a UV SO₂ camera, it is of great importance to correct the measurement for the light dilution (see Sect. 4.7), as it is, by far the strongest source of error, producing a systematic underestimation of up to 80% for very concentrated plumes, large plume-instrument distances, or hazy atmospheres (Campion et al. 2014). Two recent developments in the UV SO₂ cameras has been the replacement of bandpass filters with Fabry-Perrot interferometers (Fuchs et al. 2021), and the modification of smartphone CMOS sensors to make them UV-sensitive (Wilkes et al. 2017).

The advantages of Fabry-Perrot interferometers are an improved specificity of the instrument to SO₂, a reduction of potential interference with ozone and aerosol extinction, and a completely characterized instrumental response that makes the calibration unnecessary (Fuchs et al. 2021). The advantage of smartphone sensors is a ten-fold reduction of the instrument cost, although it comes to the price of a higher noise and/or narrower dynamic range compared to scientific grade or astrophotography cameras.

3.6 Multiple Scattering and Light Dilution

Since the time of COSPEC, it appears that scattering of UV radiation in the atmosphere was affecting the accuracy of UV spectroscopic SO₂ measurements (Millan 1980). All the above-mentioned methods calculate the SO₂ flux accurately only if the path of the light measured by the instrument is effectively equal to a straight line. In the real world, however, this is not always the case (Kern et al. 2010a), because of two processes.

First, scattering of light inside of the plume can, depending on the sun-plume-instrument geometry and on the aerosols' single scattering albedo and concentration, either lengthen or shorten the light path through the gas plume. Multiple scattering can thus cause either over- or underestimation of the actual SO₂ column density, although measurements and modelling by (Kern et al. 2012) have shown that the latter prevails in optically dense plume.

On the other hand, scattering of light that has not passed through the plume into the instrument's field of view results in an underestimation of the actual SO₂ column density. This phenomena, known as light dilution (Mori et al. 2006) increases with distance, atmospheric turbidity, and the SO₂ column amount itself.

Three classes of approaches have been proposed to tackle these problems.

- (1) Kern et al. (2012) have used a forward MonteCarlo modelling of the photon path coupled with an inversion scheme using look-up tables to retrieve both the SO₂ column density and the aerosol optical thickness of a volcanic plume
- (2) In two slightly different implementations, Varnam et al. (2020) and Galle et al. (2023) adjust a proportion of ambient skylight to the spectral fitting procedure in addition to the usual fitting parameters (SO₂, O₃, Ring and polynomial), so that the SO₂ column density retrieved in two or three adjacent

wavelength windows converges into an identical value.

- (3) Campion et al. (2015) developed a procedure specific to UV SO₂ camera measurements that estimates the scattering coefficient of the atmosphere by fitting a simplified one-directional scattering equation to the increasing lightening of topographic dark targets on the flank of the volcano at increasing distance from the camera.

4 Ground-Based OP-FTIR Measurements

Measurements of atmospheric gases using Open Path Fourier Transform Infrared (OP-FTIR) Spectrometers began in the seventies (Ackermann et al. 1976), and were brought to volcanoes in the early nineties by Japanese volcanologists (Mori et al. 1993) and then by English volcanologists (Oppenheimer et al. 1998). OP-FTIR spectrometers are used to measure the slant column densities of several volcanogenic gas species in relatively diluted plumes, a few tens to a few thousands of meters away from their source. The list of gas species that have been so far measured on volcanoes by ground-based OP-FTIR is presented in Table 2. More important than the column densities themselves, their relative abundances are the useful data for volcano monitoring, because they contain valuable information such as the volatile

Table 2 List of volcanic gases measurable by FTIR, with the common wavelength windows used in retrievals. Asterisks (*) indicate absorption measurements using infrared lamp, and italic font indicates thermal emission measurements over a cold sky background

Gas	Wavelength ranges (cm ⁻¹)	References
H ₂ O	2080–2143*	La Spina et al. (2010)*
CO ₂	6173–6390, 2063–2090*, 780–800	Butz et al. (2017), Burton et al. (2000)*, Goff et al. (2001)
SO ₂	2420–2600, 1050–1250	Mori et al. (1997), Stremme et al. (2012)
HCl	5684–5795, 2810–2890	Butz et al. (2017), Mori et al. (1997)
HF	7765–8005, 4020–4120	Butz et al. (2017), Francis et al. (1998)
CO	2000–2220	Mori et al. (1997)
COS	2000–2220	Mori et al. (1997)
SiF ₄	980–1080	Stremme et al. (2012)

abundance in the magma, its depth of residence, or possible hydrothermal interactions. FTIR measurements are also useful to quantify the emission rate of atmospheric pollutants of volcanic origin, and assess the impact of volcanism on the local and global atmospheric chemistry.

An FTIR spectrometer separates light into two beams: one is reflected on a fixed mirror and the other is reflected on a moving mirror. The two beams are then recombined, which creates a very fine pattern of constructive and destructive interferences. The detector records the light intensity resulting from these interferences as a function of the mirror position, which is known as an interferogram. The spectral properties of the beam splitter's materials and of detectors, as well as the transmittance of the Earth's Atmosphere, limit the use of OP-FTIR on volcanoes to three "windows": the Near Infrared (NIR, 0.75 to 2.5 μm or 4000–13,000 cm^{-1} to stick with the wavenumber units usually used in FTIR spectrometry), the Mid Infrared (MIR, 3 to 6 μm or 1600–3300 cm^{-1}), and the Thermal Infrared (TIR, between 8 and 13 μm or 1250–750 cm^{-1}).

Processing of OP-FTIR spectra is not as straightforward as for DOAS spectra or SO_2 camera data. First, the interferogram is converted into a spectrum through an inverse Fourier Transform. Then, synthetic spectra are modeled using a radiative transfer calculation software, and an inverse model is used to find the set of parameters that minimizes the residual between the modeled and observed spectra. However, unlike the relatively simple Beer-Lambert law that describes the radiative transfer in the UV, the modeling of radiative transfer in the IR is somewhat more complicated. The main complications are that the absorption cross sections of the gases in the infrared change significantly with temperature and pressure, and that, depending on the gas temperature and the spectral region, the emission of IR radiation by the gas can be significant, or even dominant compared to its absorption of radiation. The radiative transfer in the infrared is typically modeled by dividing the atmosphere into horizontal layers characterized

by their composition, temperature, and pressure. The transmittance of each layer is then calculated by summing the line-by-line calculation of the absorption cross-section of each gas. The radiation crossing the atmosphere is then calculated as a sum of what is absorbed and emitted by each cap. Several open source programs, such as SFIT (available at <https://wiki.ucar.edu/display/sfit4/>) or PROFFAST (available at <https://www.imk-asf.kit.edu/english/3225.php>) make these calculations transparently for the user (see review in Hase et al. 2004). However the large number of parameters to set or adjust, and the many options for fine-tuning the retrievals still require, from the person who processes the data, an amount of knowledge and experience that most volcanologists don't normally have.

Depending on which gases are targeted, and also on how close the crater can be accessed in safe conditions with a bulky OP-FTIR spectrometer (not forgetting the car battery, tripod, and laptop), several configurations of measurements can be chosen.

4.1 Solar Occultation OP-FTIR

In this configuration, illustrated in Fig. 6a, the sun is used as the source of IR radiation and the spectrometer must be aligned with the sun and the plume. The sun emits electromagnetic radiation from the UV to the Radio waves, so in theory, any spectral window where the Earth's atmosphere is transparent enough can be used. It is probably the more versatile mode of using OP-FTIR, because it can be done in any kind of volcanic activity and, if safety requires it, from a far distance to the crater. OP-FTIR measurements in the solar occultation mode are usually done in the Mid Infrared and target volcanic gases which have very low atmospheric background concentrations, particularly SO_2 , HCl , and HF . Instead, CO_2 and H_2O , the two most abundant species in volcanic gasses, are also abundant in the Earth's Atmosphere (with typical concentrations of ~420 ppm for CO_2 , and a few hundreds to a few thousands ppm for H_2O).

The light measured by the OP-FTIR spectrometer in the occultation mode has crossed the whole atmosphere, so that the atmospheric contribution to the slant column density of CO_2 and H_2O is by far superior to the contribution of a diluted volcanic plume which contains, on a thickness of less than 1 km, just a few tens of ppm of CO_2 and a few hundreds of ppm of H_2O above background. As a result, it is very difficult to measure CO_2 and H_2O in volcanic plumes with solar occultation OP-FTIR spectrometry. However, Butz et al. (2017) have shown it is possible to measure volcanic CO_2 in the near infrared (NIR), using a very precise solar tracker and appropriate atmospheric background correction procedure. It seems that volcanic CO_2 measurements with solar occultation spectroscopy in the NIR are thus possible, but restricted to strong emitters (the two volcanoes where it has so far been done, Etna and Popocatepetl, emit >2000 tons of SO_2 and >5000 tons of CO_2 per day) and still require proper validation.

4.2 Short Path OP-FTIR

Measurements of CO_2 and H_2O by OP-FTIR are less difficult if the light path is shorter than the whole atmosphere. Several measurements configurations allow to reduce the light path to a few tens or a few thousands of meters. An artificial IR source has been used in some cases (La Spina et al. 2010) for passive degassing volcanoes that are easy to access. On erupting volcanoes, where the risks are too high to make this approach possible, natural sources of infrared radiation may be used, such as a lava lake (e.g. Sawyer et al. 2008), the hot pyroclasts of a sustained lava fountain (e.g. Allard et al. 2005), or a hot wall rock from an active vent (Burton et al. 2007). The possibility to use this measurement mode (illustrated in Fig. 6b) depends on the topography of the eruptive area, but it is surely the mode that allows to remotely measure the greatest number of gaseous compounds in a volcanic plume.

4.3 Thermal Emission OP-FTIR

In the Thermal Emission OP-FTIR technique, illustrated in Fig. 6b, the spectrometer measures the Thermal Infrared Radiation emitted by the volcanic plume over a colder background (usually the upper atmosphere emission spectra). These measurements are done in the atmospheric transmittance window located between 8 and $12.5\text{ }\mu\text{m}$ (800 to 1250 cm^{-1}). At these wavelengths, only SO_2 and SiF_4 (a trace compound in volcanic plumes, but which has very strong spectral bands between 500 and 2500 cm^{-1}) are usually detected. Although H_2O and CO_2 also do emit radiation in the Thermal Infrared, their high atmospheric background concentration makes their retrieval quite complicated, as it is very difficult to separate the atmospheric contribution to their total slant column density from the comparatively much smaller volcanic contribution. Measurements of the CO_2/SO_2 ratio at Popocatepetl volcano were reported by Goff et al. (2001) in the early 2000s, but nobody has been able to repeat that since then. Even for SO_2 and SiF_4 , quantitative measurements are not easy to achieve because the amount of radiation emitted by the plume depends as much on its temperature as on its gas concentration (c.f. Eq. 3). A common assumption is to assume that the plume is in thermal equilibrium with the atmosphere at its transport altitude, but this assumption fails at the immediate proximity of the vent when the plume is still rising convectively. Another problem is that aerosols of volcanic ash and sulfates produce a broadband radiation emission that interferes with the retrievals of other gases. This effect can be corrected using advanced modeling of the Mie scattering and an inverse retrieval model (e.g. Smekens et al. 2023).

Taquet et al. (2017) have demonstrated that long-term monitoring of the SO_2/SiF_4 ratio is possible with this technique for strong emitters, such as Popocatepetl. The major advantages of Thermal Emission OP-FTIR spectroscopy are that it is well-suited for a fixed instrument and

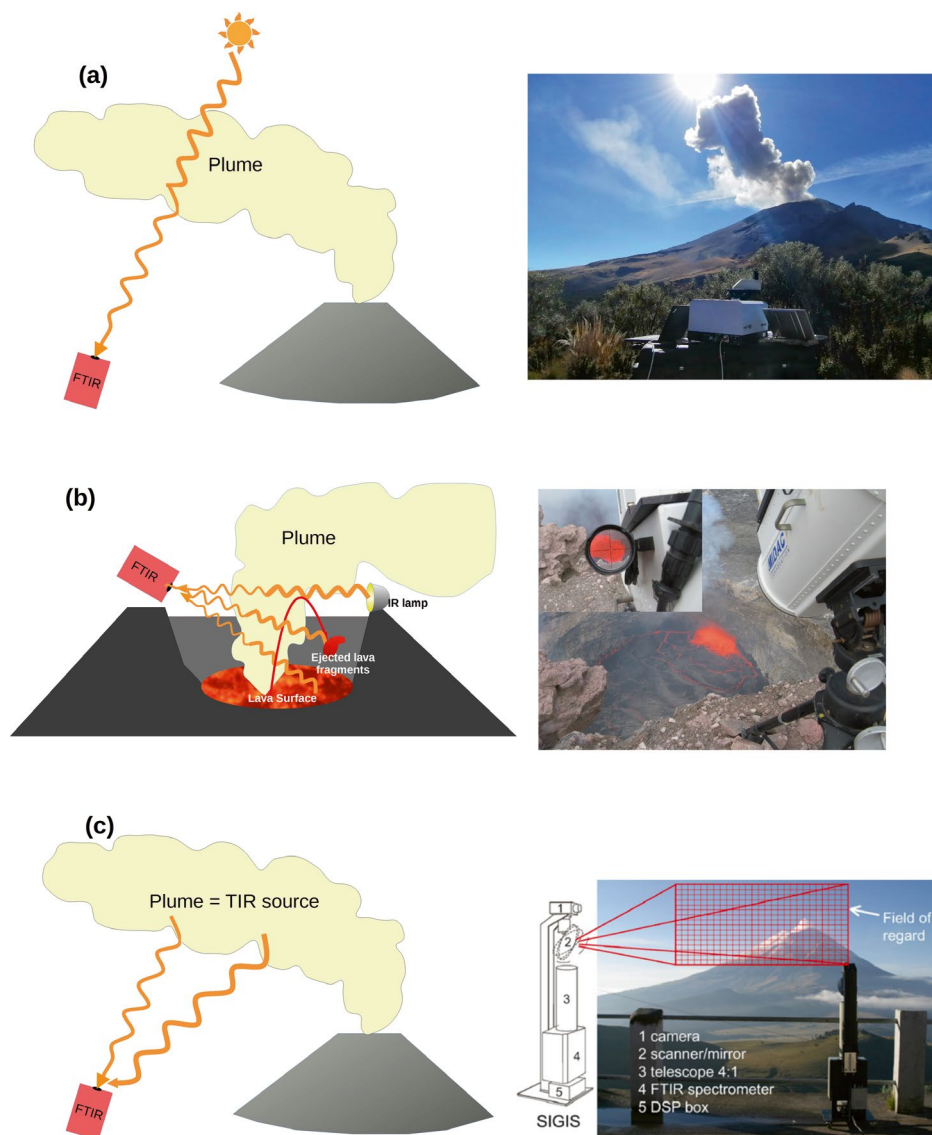


Fig. 6 Possible measurement configurations for operating an OP-FTIR to measure gases in a volcanic plume. **a** Solar occultation measurements works from any wavelength: from UV to TIR. **b** Short path OP-FTIR using an infrared lamp, airborne lava fragments, the lava itself or a hot rock surface, as a radiation source and the gas as an absorber. It is mostly used in the MIR to measure a

large number of gases such as SO_2 , HCl , HF , H_2O and CO_2 (Photo USGS, public domain). **c** Thermal emission OP-FTIR measures the thermal emission of long-wave Infrared in the Thermal Infrared (TIR) and enables to measure only SO_2 and SiF_4 but also aerosols of Sulfate and Ash (Photo taken from Stremme et al. 2012, requires permission from Copernicus)

it works equally well during the night as during the day, which opens the path to a more continuous monitoring. Especially, with the recent development of OP-FTIR spectrometers equipped with a 2D detector, it is now possible to use them to image the plume in 2D (e.g. Segonne et al. 2020), although at a lower spatial and temporal resolution than a UV camera.

5 Satellite Measurements

5.1 TOMS and the Early Development of Satellite Remote Sensing of SO₂

Satellite remote sensing of volcanic gases began accidentally (Krueger et al. 2008). In April 1982, NOAA scientists analyzing the data of the TOMS (Total Ozone Mapping Spectrometer) sensor on board Nimbus-7 noticed a huge zone of anomalous “Ozone” concentration in the plume of El Chichón volcano. It soon turned out that the actual responsible of this signal was the massive amounts of SO₂ that the eruption had injected into the stratosphere. It appeared that the spectral bands of TOMS, optimized for Ozone detection, were unintentionally, and marginally, sensitive to SO₂ as well. The successive versions of TOMS were slightly adapted to optimize the sensitivity to SO₂, which together with the decrease in pixel size, led to an improvement in their detection limit. It was later found that the ν_1 and ν_3 absorption bands of the SO₂ molecules in the Thermal Infrared (TIR) also allowed its detection by satellites (Realmuto et al. 1994; Prata et al. 2003). The technological progress in sensors, optics materials, computing, and data transmission has led to a spectacular improvement in spatial resolution, spectral resolution, sensitivity, and detection limit, as shown in Table 3, which lists the main satellite sensors that have been used for measuring SO₂.

5.2 General Considerations

The principles of satellite remote sensing techniques are broadly similar to ground-based techniques, relying on the absorption of light (whether UV or IR) by the gas molecules in the volcanic plume. Modeling of the radiative transfer in the atmosphere is thus required to obtain vertical column densities from radiance measurements. UV sensors measure the solar radiation that is backscattered by the Earth’s surface and atmosphere toward space (Fig. 7). IR sensors measure the thermal radiation emitted by the Earth’s Surface and every layer of the atmosphere including the volcanic plume (Fig. 8).

Sulfur dioxide has been the primary target for space-based remote sensing because it has a low concentration in the atmosphere background and strong absorption features both in the UV and in the IR. In recent years, satellites with improved spectral resolution and/or extended spectral coverage have been able to detect other gases, such as BrO (e.g. Theys et al. 2009), H₂S (Clarisse et al. 2011), OCIO (Theys et al. 2014), and IO (Schönhardt et al. 2017).

Two important notions for satellite remote sensing are sensitivity and detection limit. Sensitivity is the minimum value of SO₂ VCD that stands out of the background noise, and is usually calculated as three standard deviations of the SO₂ VCD in a clear region. It depends on the noise of the retrievals, which itself depends mainly on the intensity of the incoming radiation, the absorption cross-sections of the target gas and of spectral interferers, the detector noise, and the altitude of the plume. Detection limit is the smallest SO₂ mass a satellite can statistically identify as a plume. It is typically defined as a group of four (or nine) contiguous pixels having VCD above the sensitivity limit. The detection limit is thus a product of sensitivity and pixel area. The detection limit can be improved by stacking and averaging a

Table 3 Current and past space-based sensors able to measure SO₂. Pixel size increase given in the table corresponds to the nadir-viewing pixels. It increases as the viewing angle diverges from Nadir. (*) For AIRS and IASI, the value refers to the diameter of the circular footprint of the nadir pixel

Acronym	Instrument	Pixel size (km)	Operating period	Comments and reference publication
Ultraviolet sensors				
TOMS	Total ozone mapping spectrometer	62 × 62 25 × 25	1978–2004	Several versions with improving resolutions (Krueger et al. 2000)
GOME/GOME-2	Global ozone monitoring experiment	320 × 40 80 × 40	1996–2003 2006–	(Rix et al. 2008)
SCIAMACHY	Scanning imaging absorption spectrometer for atmospheric cartography	15 × 26	2002–	Partial coverage (Afe et al. 2004)
OMI	Ozone monitoring instrument	13 × 24	2004–	(Carn et al. 2008)
OMPS	Ozone mapping and profiler suite	50 × 50	2012–	(Carn et al. 2015)
EPIC-DSCOVR	Earth polychromatic imaging camera/deep space climate observatory	18 × 18	2015–	Low sensitivity, full hemispheric coverage, high imaging frequency (Carn et al. 2022)
TROPOMI	TROPOspheric monitoring instrument	5 × 3.5	2018–	(Theys et al. 2017)
GEMS	Geostationary environment monitoring spectrometer	7 × 8	2020–	Geostationary (Kim et al. 2020)
Infrared sensors				
HIRS	High-resolution infrared sounder	20 × 20	1978–	Only sensitive to high-altitude SO ₂ (Prata et al. 2003)
MODIS	MODerate resolution Imaging Spectroradiometer	1 × 1	1999–2002–	2 instruments (Watson et al. 2004)
ASTER	Advanced spaceborne thermal emission and reflexion radiometer	0.09 × 0.09	1999–	Discontinuous, programmable coverage (Urai et al. 2004; Campion et al. 2010)
SEVIRI	Spinning enhanced visible and infrared image	3 × 3	2006–	Geostationary (Prata and Kerkman 2007)
AIRS	Advanced infrared sounder	13.5 (*)	2002–	Only sensitive to high altitude SO ₂ (Prata and Bernardo 2007)
IASI	Infrared atmospheric sounding interferometer	12.5 (*)	2006–	Fourier Transform Spectrometer. 2 instruments on various platforms (Clarisse et al. 2008)

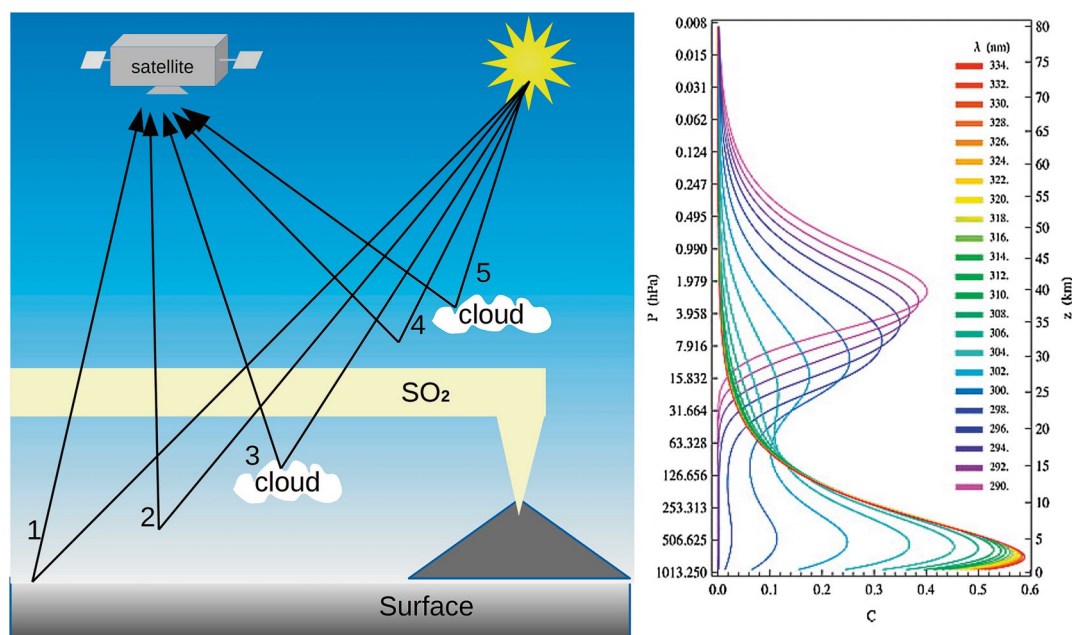


Fig. 7 Schematic drawing of the radiative transfer in the UV. Vertical scale is not respected. In the UV, the radiation that is measured by the satellite is originating from the sun and is backscattered by the Earth's surface and the different layers of the atmosphere. The Earth Surface has generally a low reflectivity (2–5%) except when it is snow-covered, so that most of the measured radiation comes from the atmosphere. Due to the much high scattering efficiency of Mie scattering, clouds, when present, are the dominant source of backscattered radiation. The presence of thick clouds above the SO₂ plume may

lower the AMF to almost 0. Conversely, the presence of clouds below the plume significantly increases the AMF. The predominance of light pathways types numbered from 1 to 3 increases the AMF, while the predominance of types 4 and 5 decreases the AMF. Due to the stronger scattering efficiency and molecular absorption of ozone at shorter wavelength, the longer wavelength UV radiation penetrates down to, and are backscattered by, deeper parts of the atmosphere, as shown in the right panel of the figure taken from Yang et al. (2010)

large number of successive images. The geographically random noise of the averaged image increases proportionally to the square root on the number of images n , whereas the SO₂ signal around the volcano increases linearly. Thus, the signal-to-noise ratio of averaged images increases by a factor $\sqrt{n}$ (e.g. Campion 2014), but at the expense of temporal resolution, which reduces the interest of this technique for volcano monitoring.

5.3 Altitude Dependence of the Retrievals

The radiative transfer has to be modelled in order to retrieve gases in the atmosphere using

space-based sensors. We hereafter describe briefly the origin and propagation of UV and Thermal Infrared (TR) radiation in order to explain the altitude dependence of SO₂ retrievals from space.

Spaceborne UV sensors measure the solar radiation that is backscattered towards the space by the Earth surface, the atmosphere's molecules and clouds. The retrieval of SO₂ is usually performed in two steps. In the first one, the spectral data are processed to obtain the Slant Column Density (SCD), using either a DOAS-like methodology (e.g. Yang et al 2007; Theys et al. 2017) or a statistical approach based on principal component analysis (Li et al. 2013) or covariance (Theys et al. 2021). The latter have been preferred in recent years due to

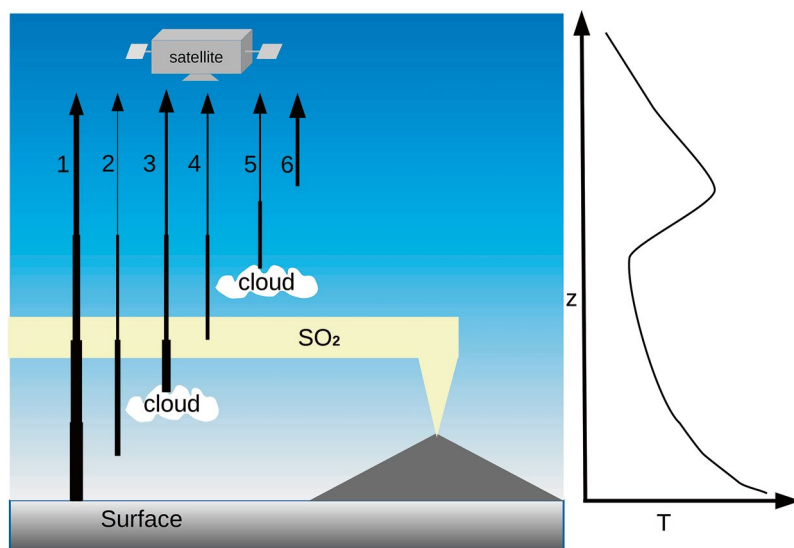


Fig. 8 Schematic drawing of the radiative transfer in the IR. The radiation, represented by upwards arrows whose thickness is proportional to intensity, is emitted by the Earth's surface and the different layers of the atmosphere and is absorbed by the overlying ones. The intensity of the radiation emission depends on the temperature (which depends strongly on the altitude z), pressure and

concentration of the different molecules in the layer. The intensity of the radiation absorption depends on the pressure and concentration of the different molecules in the layer (Beer-Lambert's law). The consequence of this is that the plume neat absorption depends on its concentration and its temperature (and hence altitude)

their enhanced sensitivity. In the second step, the Slant Column Density is divided by the Air Mass Factor to obtain the Vertical Column Density. The Air Mass Factor corrects for the effect of how the radiation propagates into the atmosphere. It depends mostly on the satellite viewing angle, the solar zenith angle, the altitude of the plume, the fraction of the pixel occupied by clouds and their mean altitude, the Earth surface albedo, and the abundance of vertical distribution of aerosols (Theys et al. 2017). Air Mass Factors are usually calculated offline once and for all using radiative transfer models (see review in Lorente et al. 2017), to form large look-up tables that are functions of all these parameters. Then, they can be interpolated for each pixel knowing the geometry of observation, retrieved parameters for this pixel (ozone VCD, cloud fraction and altitude, etc.), and some a priori information (e.g. plume altitude, seasonal aerosol distribution). From this a priori information, the most critical one is probably the plume altitude, because of its wide natural variability

and its strong effect on the retrievals. The lower the plume, the higher amount of radiation will be backscattered by the overlying atmosphere and the lower amount will cross the plume and be actually absorbed by the SO_2 molecules it contains.

To model the radiative transfer in the infrared, the atmosphere is divided in a number of superposed horizontal layers whose temperature and gas concentration vary with altitude. As shown schematically in Fig. 8, each layer absorbs the radiation coming from below depending on its pressure and concentration of the different molecules (Eq. 2), and emits radiation depending on the temperature, pressure and concentration of the different molecules in the layer (Eq. 3). Thus, the temperature of the plume, determines its neat absorption (the balance between the absorption and emission of radiation). Since the temperature normally decreases with altitude in the troposphere, the higher the plume, the stronger its neat absorption.

Operational algorithms that generate near-real-time SO₂ products available on-line use several a priori plume altitudes to retrieve different SO₂ VCDs under these hypothesis. The end-user of these products can easily calculate the “true” SO₂ VCD by interpolating these model values at the best-estimated plume altitude (either from visual observation, trajectory modelling, LiDAR data, or other). When doing so, the user has to remember that an overestimation of the plume altitude causes an underestimation of the calculated SO₂ VCD.

More sophisticated algorithms can simultaneously retrieve the SO₂ VCD and the peak of its vertical distribution by fully exploiting all the information contained in applied to high spectral resolution satellite data. In the infrared, these algorithms are mostly based on the quantification of the pressure-induced broadening of SO₂ absorption lines in the spectra of volcanic plumes (e.g. Clarisse et al. 2014, for IASI). In the Ultraviolet, they are based on the spectral dependence of the radiation absorption (e.g. Yang et al. 2010, for OMI) due to the deeper penetration of longer wavelength radiation in the atmosphere.

5.4 Deriving SO₂ Emission Rate from Satellite Data

Satellites basically provide a 2D distribution of SO₂ VCD. From this, assuming that its vertical distribution is reasonably well known, it is relatively easy to calculate the SO₂ mass around the volcano, by summing the individual masses of all the pixels within a certain radius from the volcano which have their VCD above a certain threshold that depends on the sensor sensitivity (e.g. Carn et al. 2008; Valade et al. 2019). The SO₂ mass is a useful information in case of a short-lived eruptive event. However, for eruptions lasting more than a day, or for permanently degassing volcanoes, the SO₂ mass depends on a number of factors unrelated to the volcanic activity: the completeness of the plume’s coverage by the satellite image, the masking of some parts of the plume by higher

meteorological clouds, the reaction speed of the SO₂ in the atmosphere, and the dispersion of the plume by regional winds until it passes below the detection limit. Instead, the SO₂ emission rate is usually the physical quantity that interests volcanologists. In this section, we briefly review the different methods to derive SO₂ emission rates from satellite images. The reader can find in Theys et al. (2013) a more complete description of each of them and their application to several case studies of eruptions with various sensors.

5.4.1 The Mass-Length-Speed Method

The Mass-Length-Speed method (e.g. Lopez et al. 2013), arguably the simplest one, consists of multiplying the SO₂ mass present in the plume by the wind speed at the plume altitude and dividing this product by the plume length. This method provides a unique emission rate estimate over a considered time interval and assumes a constant wind speed and a known plume altitude.

5.4.2 The Traverse Method

The traverse method is an adaptation to satellite images of the approach used in ground-based mobile measurements. The SO₂ flux is calculated over rows or columns of pixels that cross the plume as

$$F = \left(\sum_i X_i l_i \right) * \sin \theta * v \quad (18)$$

where l_i is the along-track or cross-track pixel size, depending on the wind direction, and θ is the angle between the wind direction and the line of pixel, and the other symbols the same as in Eqs. (5) to (8).

The advantages of the Traverse method are its ease of implementation, the possibility, for simple wind fields, to calculate the time of emission of the different parts of the plume based on their distance to the vent, and therefore to obtain flux time series with a sub-hourly resolution (Merucci et al. 2011), and the ability to exclude some parts of the plume from the calculation based on objective criteria of cloud fraction and altitude. The disadvantages of the Traverse

method (and of the Mass-Length-Speed method as well) are that it requires a priori knowledge of the plume height and transport speed, and that it is imprecise and inaccurate when the plume is dispersed by a weak or shearing wind field.

5.4.3 The Delta-M Method

The Delta M method, introduced in Theys et al. (2013), is based on a mass balance equation stating that the time series of SO₂ mass measured by the satellite in the plume of a long-lasting emitter corresponds to the SO₂ that has been injected between the two overpasses minus what has reacted with the atmosphere, assuming a first-order reaction rate for SO₂.

The flux is thus calculated as

$$F = k \cdot \frac{M(t) - M(t - \Delta t) \cdot e^{-k \cdot \Delta t}}{1 - e^{-k \cdot \Delta t}} \quad (19)$$

where $M(t)$ is the SO₂ mass at time t , Δt is the time difference between two overpasses, and k is the first-order reaction rate constant of the SO₂. The advantage of this method is that it does not require any knowledge of the transport speed of the plume, which makes it useful for cases where the wind field is weak, shearing, or poorly constrained. The disadvantages are that the method requires the whole plume to be imaged by the satellite and that the result depends strongly on the assumed value of reaction speed of the SO₂. Two main reaction pathways remove SO₂ from the Earth atmosphere: the dissolution into water droplets from the clouds and precipitation, and the gas phase oxidation by the OH radical and ozone (see Eatough 1994 for a review). The former is much more efficient but requires the presence of clouds, while the latter is ubiquitous during day but limited at night due to the strong diurnal cycle of these compounds. Thus, the overall removal speed of SO₂ from the atmosphere varies greatly according to atmospheric humidity, the presence of particulate matter, and the intensity of solar radiation, resulting in atmospheric lifetime of a few hours to a few days. Nevertheless the Delta-M approach may be promising to apply for future geostationary instruments such as Tempo (Zoogman et al. 2017) and IASI-NG (Crevoisier et al. 2014) due

to their very wide coverage and high temporal resolution.

5.4.4 The Inverse Modelling Methods

Volcanic eruptions can inject SO₂ into the atmosphere at a range of altitude that is often poorly constrained. In all the previous approaches, the altitude of injection has to be assumed, with an uncertainty that has consequences on the accuracy of the retrievals (see Sect. 6.3). After its injection, the plume is transported by the regional winds, whose direction and speed depend on the altitude(s) of injection and time. The 2D SO₂ distribution that results from that transport can be inverted to gain time-resolved information on both its emission rate and injection height distribution. Two approaches have been used:

- (1) An inversion of the linearized direct transport model (e.g. Stohl et al. 2011) using an optimal estimation method.
- (2) An iterative back-trajectory simulation for every pixel containing SO₂. Using the proximity of the back-trajectory to the vent coordinates as a convergence criterion for constraining the time and height of the emission of the gas that the pixel contains (Pardini et al. 2017; Esse et al. 2023).

Both approaches are especially useful in case of a large eruption that injects SO₂ in a wide range of altitude and/or in case of strong vertical wind shear. However, they require a good knowledge of the wind field for the simulation to converge and may give non-unique solutions in case of low wind shear. The masking of parts of the plume by higher atmospheric clouds also generates systematic underestimation of the emission rate in some periods of the time series.

5.5 Synergy Between Satellite and Ground-Based Data

Thanks to the continuous improvement in sensor technology, the detection limit of some satellites, such as Tropomi, is now low enough to

enable a reliable monitoring, on an almost daily basis, of the SO_2 emissions from volcanoes that emit more than 10 kg/s of SO_2 (see the example of Popocatepetl, in Fig. 9). However, because of their limitations in the available light, satellite sensors have a lower detection limit than ground-based instruments. Ground-based instruments are usually placed close to the volcano and, when the plume is ash-rich and/or very concentrated, present limitations inherent to the radiative transfer in almost opaque plumes. Satellites, instead, are less affected by these limitations because they offer the possibility to

measure the SO_2 flux further downwind of the volcano, where part of the ash has already settled, and where the plume has been diluted enough so to avoid radiative transfer problems. Satellite measurements also allow a synoptic, worldwide view of volcanic degassing, which includes remote and unmonitored volcanoes (e.g. Carn et al. 2017). Satellite and ground-based measurements should thus be used in a synergic manner to maintain a high accuracy all over the time of an eruptive crisis. However, to achieve that, more work is necessary to cross-compare satellite- and ground-based data on

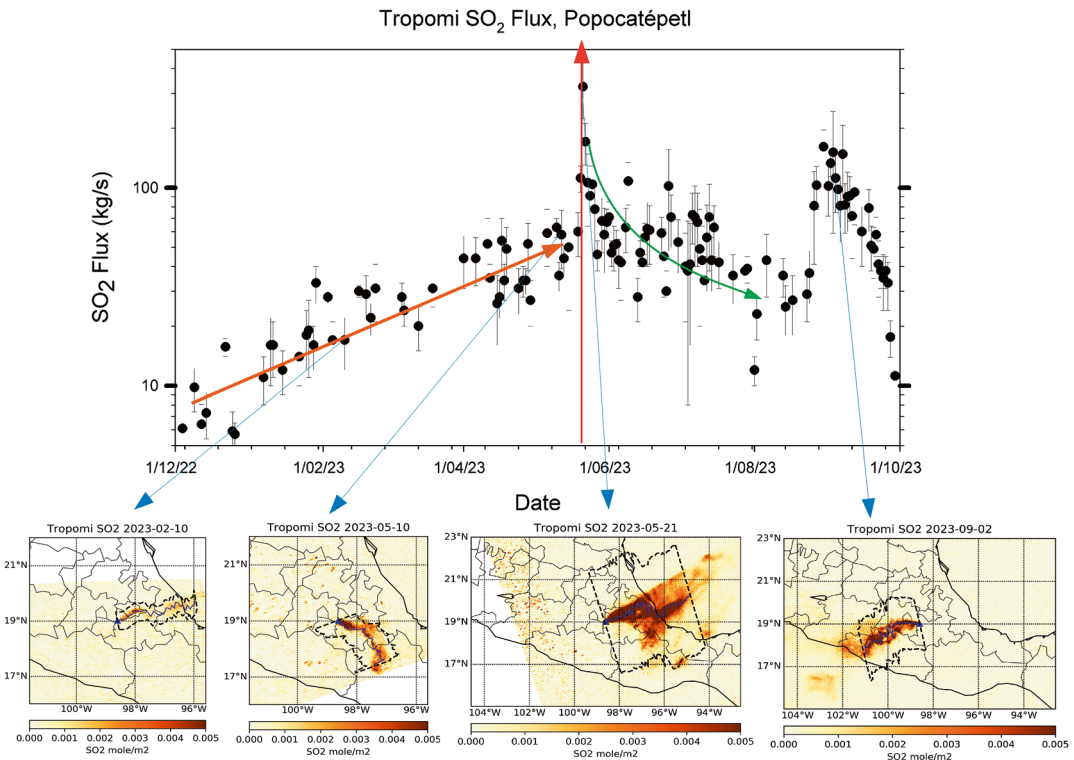


Fig. 9 Routine daily SO_2 flux measurements from Popocatepetl volcano, obtained by processing the images of Tropomi with the Traverse method. The measurements precision is high enough to clearly identify interpretable trends for volcano monitoring. A gradual four-fold increase from January to May 2023 (orange arrow) was the symptom a recharge in juvenile magma in the feeding system. The brutal increase on May 20th 2023 (red arrow) accompanied a sustained explosive eruption that marked the arrival of this magma at the surface. During the decrease phase that followed, the activity was alternating between episodes of sustained (but less intense)

explosive activity and passive degassing. The decreasing trend (green arrow) was interpreted as a gradual depletion of the magmatic volatiles. The reappearance of high SO_2 fluxes in September 2023 was probably due to an event of second boiling that triggered new episodes of sustained explosive activity, but these were shorter and less intense than those of May–July. A few images representative of each phases are displayed below the time series graph (which is in logarithmic scale). These results, obtained in near-real-time by the author, took a large part in the assessment and management of the evolving eruptive crisis

volcanoes that present SO₂ emission rates in the range where both classes of methods give relatively reliable values (10–100 kg/s).

6 Interpreting the Data

Remote sensing of volcanic gases is an essential part of volcano monitoring, but its usefulness is obviously restricted to volcanoes that emit significant amounts of gases, either from fumaroles, from open-vent passive degassing, or from eruptive activity. On these volcanoes, it provides crucial information that no other geophysical technique can obtain such as the gas content of the magma, the magma feeding rate, or the sealing of the conduit. However, one has to keep in mind that, unlike geophysical techniques, the gas data are inevitably discontinuous, because their availability depends on intrinsically variable conditions such as visibility, UV radiation, or wind conditions. The key for interpreting the data is a good understanding of the processes that affect the composition and emission rate of the gases and the timescale on which these processes are able to act.

6.1 Interpreting Gas Composition Data

The composition of the gases emitted depends mainly on the following factors.

(1) The geodynamic context

Subduction zones magmas are generally richer in volatiles, especially water and halogens. Hot spot magmas are generally poorer in volatiles (with some notable exceptions as in the Canary Islands), and richer in Carbon and Sulfur. Primitive Oceanic Ridge magmas are volatile-poor but relatively richer in Carbon and Sulfur (e.g. Review in Giggenbach 1996). Magmas from continental rifts are notably rich in Carbon, to the point that evolved magmas from continental rifts may sometimes generate immiscible

carbonatitic melts at the end of the magmatic differentiation.

(2) The composition and previous degassing history of the magma.

Primitive basaltic-like magmas are relatively richer in Carbon and, to a lesser extent, in Sulfur. Carbon dioxide exsolves at greater depth and earlier than any other major volatile species, so that an increase in carbon dioxide flux (either diffuse or in the plume) is often among the first precursors of an injection of juvenile magma in the deep plumbing system of a volcano (e.g. Aiuppa et al. 2017; 2018; This Volume). Instead, magmas that have already been partly degassed are carbon-poor and enriched in halogens (e.g. Taquet et al. 2019), because of the much higher solubility in silicate melts of these latter elements.

(3) The depth of residence of the magma that degasses.

Volatiles have differential solubilities in silicate melts that usually go in the following order: $C < S \leq H_2O < HCl < HF$. As a result, the equilibrium composition of the gas that exsolves from the magma is a function of the pressure, and hence depth at which magma resides. Allard et al. (2005) could measure, with OP-FTIR, an increase in CO₂/S and S/Cl during lava fountain episodes in Etna, and infer a deeper origin of gas than during strombolian activity. Conversely, episodes of lava dome growth at Soufriere Hills (Edmonds et al. 2001) or Popocatepetl (Taquet et al. 2019) are accompanied by a marked increase in HCl/SO₂ and HF/SO₂, because of the shallowing of the magmatic source of halogen.

(4) Hydrothermal processes.

Magmatic gases may have to percolate through a thickness of several km of rocks whose pores are often saturated with liquid vapour or supercritical water, and which are known as hydrothermal systems (See Aiuppa et al., this volume for more detail). The chemical reactions

between magmatic gases and these systems cause profound transformations of their composition on their way to the surface. Water-soluble compounds such as SO_2 , HCl , HF , and to a lesser extent CO_2 will dissolve into the hydrothermal fluid. Other gasses, initially absent or little abundant in the purely magmatic gases, such as CH_4 and H_2S , are formed by reaction with the fluid, or with minerals in the hydrothermal system (e.g. Symonds et al. 2001). However, CH_4 is usually not abundant enough to be detectable by remote sensing, while the detection of H_2S is hampered by spectral interferences with water vapour.

(5) Mixing of gases from different sources.

Remote sensing of volcanic gases is usually implemented on relatively diluted volcanic plumes, which can result from the mixing of different sources, e.g. a magmatic source coming from a high-temperature vent or eruptive activity, and a hydrothermal-dominated source coming from low-temperature fumaroles or diffuse degassing (e.g. Bataglia et al. 2018). This mixing between two (or more) chemically very different components is governed by atmospheric advection processes, which are notoriously turbulent, and therefore generates a variability in the gas composition data that mostly operates at short timescales (~minutes), but may also contain slower variations (intra-day to multi-year) due to the changes in wind regime.

6.2 Interpreting SO_2 Flux Data

The emission rate of SO_2 and its variations, which span timescales from seconds to years, can also provide useful information for volcano monitoring and for deciphering the processes that occur in its plumbing system. Dormant volcanoes or volcanoes with low temperature ($<100^\circ\text{C}$) fumaroles typically do not emit SO_2 . Volcanoes emitting between 10 and 100 T/d are considered as small emitters. These are typical of high-temperature fumarolic fields (e.g. Taran

et al. 2018), or small scale magmatic activity. Values between 100 and 1000 T/d are considered as moderate, and characterised many small-scale eruptions and open-vent volcanoes (e.g. Carn et al. 2017). Values between 1000 and 20,000 T/d are considered as high. They are typical of large lava lakes at the early stage of their formation (Campion and Coppola 2023), and moderate eruptions. Values over 20,000 T/d are considered as extreme, and encountered only rarely, in intense eruptions or very high passive degassing. The largest SO_2 release by an eruption was measured during the climatic plinian eruption of Pinatubo (~19 MT, Guo et al. 2004) in 1991. The highest measurements of SO_2 produced by passive degassing (~200,000 T/d) were obtained at Popocatepetl volcano (Delgado-Granados 2008) and Miyake-jima (Kazahaya et al. 2004).

When gases are transferred directly from the magma to the atmosphere with no hydrothermal interaction, their emission rate often reflects the magma feeding rate of the volcano. That magma feeding rate can be calculated with a simple equation:

$$F_m = \frac{M_S \cdot F_{\text{SO}_2}}{M_{\text{SO}_2} \cdot (CS_0 - CS_m) \cdot (1 - X_{ci})} \quad (20)$$

where F_{SO_2} is the SO_2 emission rate, CS_0 is the initial mass fraction of Sulfur in the magma (estimated from the analysis of the most primitive magmatic inclusions available for a given volcanic system, e.g. Metrich and Wallace 2008), CS_m is the residual mass fraction of Sulfur in the melt, M_{SO_2} and M_S are the molar masses of SO_2 and S, and X_{ci} is the initial crystal content of the magma. The generalization of these calculations for many different volcanoes and eruptions in the world led volcanologists to highlight an almost systematic imbalance between the degassed magma and the magma that is actually emitted (see reviews by Shinohara 2008 and Edmonds et al. 2022). The amount of magma required to account for the observed SO_2 fluxes is almost always greater than the magma that is actually erupted at the

surface. For eruptions, this sulfur excess was interpreted to result from the accumulation of an exsolved C-O-H-S vapor phase in the upper part of magma storage system prior to the eruption (Wallace 2001). For the volcanoes which present long-term passive degassing, in which the sulfur excess is the strongest, it is believed that convection processes (Kazahaya et al. 1994) bring the juvenile magma at shallow depth, where it degasses, before bringing it back to the deep storage area, where it may form cumulates or deep dykes (e.g. Allard 1997).

From Eq. 20, long-term (months to decades) variations in the SO_2 emission rate over time can have two possible magmatic origins: either a change in the magma supply rate or a change in the Sulfur concentration in the magma. The gradual outgassing of a magma batch residing at depth usually produces a slow reduction in the SO_2 flux. Alternatively, more superficial processes can affect the transfer of magmatic gases from the area(s) where they exsolve to the surface. For example, a decrease in the SO_2 flux can be caused by either conduit sealing or hydrothermal scrubbing.

Sealing can be defined as a decrease in the permeability of the pathway(s) that gases take from their exsolution to the surface. Various sealing mechanisms have been proposed such as magma crystallisation (e.g., Stix et al. 1993), cooling and rheological stiffening (e.g. Nadeau et al. 2011), hydrothermal alteration and precipitation of minerals in pores and fractures (Heap et al. 2019; Mick et al. 2021), the filling of fractures with ash particles and their further sintering (Kendrick et al. 2016), or the compaction of the porous or fragmented hot conduit material by the lithostatic pressure (Okumura et al., 2014; Campion et al. 2018). The timescale of the former three processes spans days to years, whereas that of the latter two spans minutes to hours.

Hydrothermal scrubbing (Symonds 2001; de Moor et al. 2016) is also a process that, when the hydrothermal system is large, thick and water-dominated, can efficiently dissolve the SO_2 and form dissolved sulfate ions (found in hot spring

around the volcano), and native sulfur or H_2S through the disproportionation reaction (e.g. Kusakabe et al. 2000). Recent studies compiling chemical composition of gases, mineralogical evidences and thermodynamical modelling (Henley and Fischer 2021) suggest that SO_2 can also be sequestered at shallow depth as anhydrite and sulfide minerals. Thus, unlike sealing, scrubbing causes profound changes to the composition of the gases emitted at the surface. The response of a large and well-developed hydrothermal system to a series of magmatic intrusions could be documented in detail at Turrialba Volcano (Costa Rica). The initial phase of heating and drying out was a slow and gradual process that took several years (Vaselli et al. 2010), but its by-pass through a phreatic eruption that opened a new conduit was very rapid (Campion et al. 2012). The recovery of the hydrothermal system after a phase of magmatic activity took a few months (de Moor et al. 2016).

Advancing further from the slow processes with a deep magmatic origin and the fast processes with a conduit or hydrothermal origin, SO_2 cameras have opened new perspectives by allowing to access the super fast variations (up to a second) of SO_2 emission rates, correlate them to geophysical observations (see review in Platt et al. 2018), and tentatively model conceptually (e.g. Moussalam et al. 2016) or even numerically (e.g. Pering et al. 2016) multiphase flows in the conduits.

7 Current Challenges and Perspectives in the Discipline

The development of remote sensing of volcanic gases has followed an exponential trend, with a relatively slow -and late- start and a spectacular acceleration since the early 2000's. Nothing indicates that it will stop soon. An emerging tendency, favoured by the technological progress in sensors sensitivity and spectral separation techniques, is that the new instruments are now bridging the gap between high spectral

resolution and high imaging resolution without compromising sensor noise or temporal resolution. This is true for the last generation of space-based sensors. Tropomi measures SO₂ and BrO with a spatial resolution that is only a small fraction of its predecessors. Tempo, launched in April 2023 on a geostationary platform, will provide real-time UV monitoring of SO₂ emissions 10 h per day for volcanoes of North America and the Caribbean at a spatial resolution equal or superior to that of OMI. IASI NG, and Sentinel-4 will do the same, in the Infrared, for the volcanoes of Europe and GEMS is already operating over those of Northern Asia.

For ground-based sensors, one of the current challenge is the retrieval of SO₂ in ash laden plumes, especially in proximal plumes, which are often completely optically thick due to ash or sulfate aerosols. Hyperspectral cameras and OP-FTIR spectrometers equipped with a focal plane array detector are also getting more and more used for multi species retrievals (SO₂, ash, sulfate aerosols, SiF₄) that have less cross interferences between them (e.g. Smekens et al. 2023). The recent application of Fabry–Perot interference filters to UV-cameras and spectrometers also opens exciting perspectives in imaging measurements of more volcanic gases than SO₂ (Kuhn et al. 2023). For really dense plumes where the method based on UV or IR spectroscopy may fail, microwave spectroscopy could be a promising option in the future. It has been applied to measure SO₂ from a powerful microwave Earth-based telescope and study the sulfur chemistry in the very thick atmosphere of Venus (Sandor et al. 2010).

Acknowledgements I acknowledge the funding organisms that have supported my research. FRiA and Vocatio in Belgium and CONAHCYT (through project number A1-S-30127) and DGAPA-PAPIIT (IA103816 and IN112923) in Mexico. I also thank all the people who shared their knowledge with me during all these years: Michel van Rozendaal, Caroline Fayt, Lieven Clarisse, Daniel Hurtmans, Fred Prata, Toshiya Mori, Christoph Kern, Wolfgang Stremme, Noémie Taquet, Hugo Delgado, Stefano Corradini, Alain Bernard and many others.

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Monitoring Lava Flows

Oryaëlle Chevrel and Andrew Harris

Abstract

A volcanic effusive event needs to be monitored to assess the possible impacted area. To achieve this, a number of measurements need to be made either from the ground, from the air, or from interpretation of satellite imagery. These measurements need to be made through established protocols so that derived parameters can be calculated and used to contribute to forecasting and mitigation measures. Key source term parameters include vent location, discharge rate, flow velocities (at-vent, down system, and flow front), feeder system, dimensions (thickness, length, width, underlying slope), feeder system thermal conditions (well-insulated or poorly insulated), and lava temperature, crystallinity and rheological state. First order needs are slope, discharge rate velocity, cooling rate, petrology and rheological characteristics. These are

the source terms needed to assess and model lava flow hazard. In this chapter, we review the measurements that are typically made and the subsequent derivatives that can contribute to monitoring activities during an effusive event.

1 Introduction

In this chapter, we review the measurements that are typically made to contribute to monitoring activities during an effusive event. These fall into three linked categories which will provide information for reporting. They are (Fig. 1):

1. Measurements that need to be made in the field;
2. First order derivatives which are derived from data collected in the field or via remote sensing; and
3. Second order derivatives that use the first order product to carry out model-based projections.

Thus, these steps can feed a fourth level of modelling that contributes to forecasting and feeds back into the reporting (Fig. 1).

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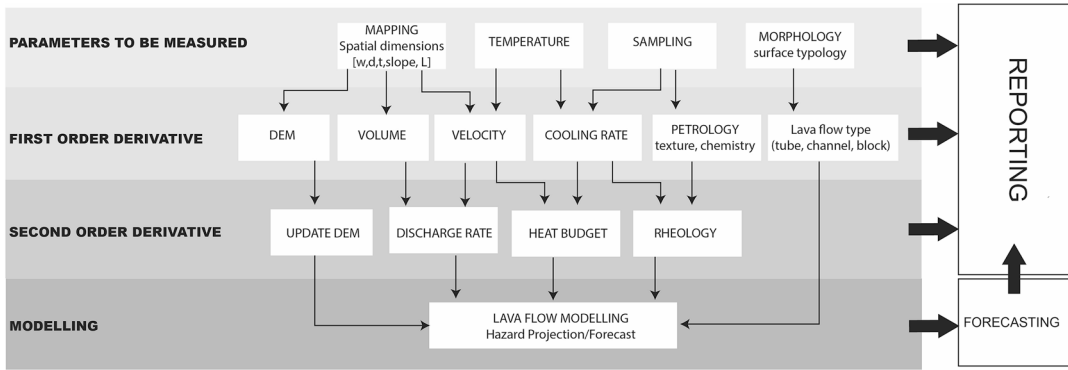


Fig. 1 Flow chart tracking the series of measurements and calculation of derived parameters that are typically made to contribute to monitoring activities during an effusive event

1.1 Type of Lava Flows and Associated Hazard

1.1.1 Lava Flow Types

Lava flows are gravity currents that propagate downslope under their own weight, with resistance to flow being due to the flow viscosity and yield strength, both of which increase with cooling and crystallization. Flow velocity, width and length mainly depend on the effusion rate (i.e., lava volume flux leaving the vent at any given point in time), plus the topography over which the lava extends and the thermo-rheological properties of the lava. Typically, the higher the rate of effusion the longer the flow, and the lower the viscosity and the steeper the slope, the faster the flow moves. Advance stops when the supply of lava stops (volume-limited flow) or when cooling is such that the flow viscosity reaches a limit that prevents further motion (cooling-limited flow).

Basaltic flow types, that we consider here, are generally pāhoehoe, with a smooth, coherent surface, or ‘a’ā with a surface comprising a layer of clinker. Basaltic lava flows can be channel or tube-fed, and may extend a few to a few tens of kilometers. Tube formation insulates the lava, reducing cooling rates and allowing the lava to extend greater distances, where the longest lava tubes on Earth are more than 100 km long. More siliceous compositions (andesite, dacite and rhyolite) are more viscous and their advance rate

is slower. Their thickness is generally tens of meters and their surface is often made of angular blocks which can reach sizes of the order of a meter. Silicic lava flows can, though, extend several kilometers, where flow front collapses can depressurize the flow interior to feed pyroclastic flows of the block-and-ash type.

1.1.2 Associated Hazard and Risks

Lava flows do not represent a major volcanic hazard, and they rarely pose a safety risk to populations (Harris 2015). However, they do (on occasion) cause injury and fatality. The deadliest examples are those of the Nyiragongo eruptions in the Democratic Republic of Congo (DRC) in 1977, 2002 and 2021. These eruptions involved extremely fluid lava flows that moved at high velocities and reached the city of Goma, 10 km to the south of the source vents, in just a few hours. These eruptions each accounted for several tens of fatalities, from direct contact with lava, collapse of buildings, and/or explosion of fuel tanks.

These losses are minimal compared to those of other volcanic phenomena (they represent only 0.2% of the total deaths linked to volcanic hazards—(Harris 2015)), but nonetheless lava flows destroy, burn and bury all infrastructure and vegetation in their path, having lasting effects on local economies. The 2018 effusive eruption of Kīlauea in Hawaii which lasted only 4 months (Neal et al. 2019) caused no casualties, but destroyed more than 700 houses and

caused losses estimated at over \$800 million (Meredith et al. 2022). The 2021–2022 eruption of La Palma (Canaries), buried ca. 1200 ha of land including agricultural land and villages, destroying more than 1600 houses and involving displacement of more than 7000 people (Cabildo de la Palma: <https://riesgovolcanico-lapalma.hub.arcgis.com>).

When the lava comes into contact with water, the instantaneous thermal expansion of the water causes littoral explosions, while persistent entry of lava into the ocean can build benches. Benches are unstable, and often collapse so that ocean entry sites are extremely dangerous for visitors. Vaporization of sea water at ocean entries also feeds persistent gas plumes named laze. Laze and gas plumes associated with emission of lava at the vent, that create a volcanic smog (vog), are loaded with fine particles, as well as harmful gases and aerosols (HCl, CO₂, NO₂ and SO₂; (Hansell and Oppenheimer 2004). At source, they are also extremely hot so that inhalation of the vapor can be fatal due to extreme lung damage. Wet and dry acid deposition can also damage to infrastructure, through corrosion, as well as to crops, forest and habitat (Blong 1984; Schmidt 2015).

1.2 Spatial Coverage, Time Scales and Definitions

1.2.1 Spatial Coverage, Time Scales

Lava flow monitoring can be carried out from three locations: ground, air and space. Each vantage point allows differing spatial coverage and time scales of change to be tracked, increasing from local and rapid for the ground observer to synoptic and regular from satellites. Ground-based surveys include rapid, real-time measurements usually focus on the key elements of the flow field: the vent, the master channel or tube, and flow front. Ground-based surveys are usually carried out on foot, and have increasingly been supported by surveys by unmanned aerial systems or vehicles (UAS-UAV, see review from James et al. 2020). UAS surveys cover a few

m² to hundreds of m² and are performed from heights of typically ≤ 120 m. This allows greater coverage, is faster than walking the edge of a flow unit, and allows access to zones that are impossible to approach on foot. However, like measurements made on foot, UAS surveys cover only a restricted time slot of a few minutes.

Airborne surveys are measurements performed from helicopter or any aircraft and cover area of few km² to 10's km². These operations are performed from higher altitudes, between 300 and 1500 m, than via UAS and may be run over several hours.

From space, satellite-sensor based acquisition includes geostationary as well as polar orbiting satellites allowing synoptic coverage at wavebands spanning the ultraviolet, through the visible to the infrared and radar. However, only the latter is not affected by cloud cover.

Effective monitoring of lava flows combines observations from each of these three locations. Observations are complementary, and ideally data acquired from all three locations are combined to ensure a full temporal and spatial coverage of the advancing lava flow. For example, while the ground-based observation can be used to ground truth a point or area within a satellite-sensor-derived image, the image can be used to extend knowledge beyond the isolated points visited on the ground.

1.2.2 Definition of Source Terms

A key source term for lava flow monitoring is the volumetric discharge rate (in m³/s). This has three definitions depending on the temporal scale over which the flux is measured (Fig. 2a; see also Harris et al. 2007a, b):

1. *Instantaneous effusion rate (IER)*: This is the volume flux measured at any single point in time. It is primarily measured in the field at the master channel or tube using the cross-sectional area (in m²) of the flow multiplied by the flow velocity (in m/s).
2. *Time-averaged discharge rate (TADR)*: This is the volume flux averaged over some period of time. This is the value typically obtained

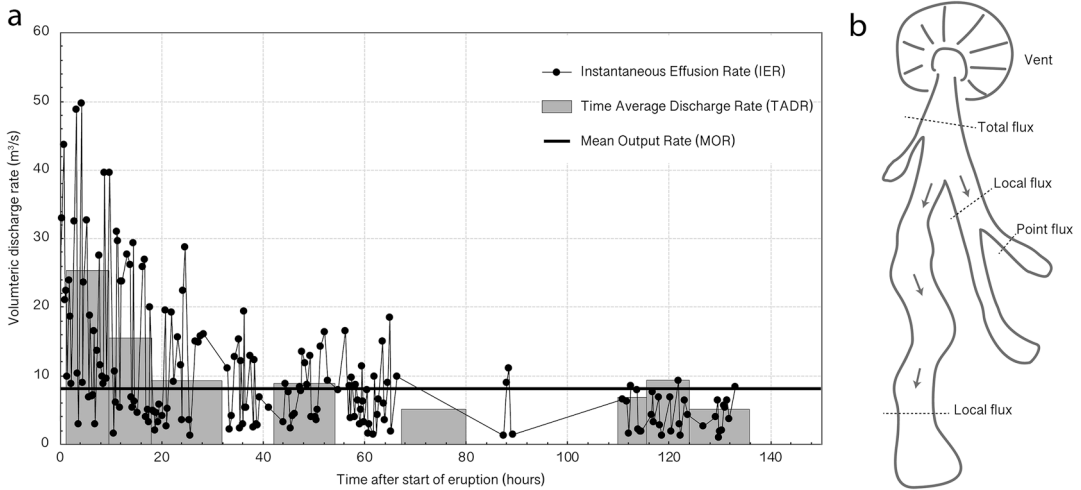


Fig. 2 Discharge rate definition over **a** time and **b** in space

from satellite infrared data or from DEM subtraction during the eruption. In this latter case, the volume of the lava flow field on day n is subtracted from the volume of day $n+i$. The residual volume is then divided by the time between the two measurements to give the time-averaged flux during the i days between the two volume measurements.

3. *Mean output rate (MOR)*: This is the total volume erupted during the entire eruption, or eruptive phase (usually obtained by DEM difference pre and post eruption), divided by the duration of the eruption.

As we move through these measurements, the discharge rate curve becomes increasingly smoothed and we lose the detail of peaks and troughs (Fig. 2a). The absolute value of the peak fluxes also becomes reduced, which is something to bear in mind when applying predictive models that relate volume flux to flow runout.

The flux measurement will also be influenced by where in the system the measurement is made (Fig. 2b). The *total* volume flux can only be measured at the master channel or tube exiting the vent and through which all of the volume passes. In a bifurcating system, after the first branch a *local* flux will be measured which will be less than the total flux as the volume is beginning to be partitioned between

different distributaries. Finally, a *point* flux will be obtained at a flow front lobe when many lobes are active (Fig. 2b).

We need also to distinguish between bulk and dense rock equivalent (DRE) volume fluxes. The bulk measurement includes all fluid and bubbles, as well as cracks in solid lava and spaces between clasts in an 'ā'a flow. In contrast, the DRE only considers the solid phase and does not include bubbles. This can be quite an issue as at the vent bubble contents can be very high and usually decreases toward flow front. Worse, bubble contents can vary with time during an eruption. Thus, volume flux measurements should always be taken, or reported, in tandem with a measure of the bubble content. As a result of all inherent sources of error, the uncertainty on a volume flux measurement is often at least 50%. Thus, numbers (below) 100 should be reported to the nearest decimal place; above 100 to the nearest round number; and above 500 to the nearest ten, etc.

Finally, the spatial position of flow velocity needs to be well defined because it changes down system depending slope, flow depth and rheology. Fundamentally, channel velocities measured at any given point down system will be higher than the flow front advance rate, with the latter measurement being fundamental for hazard assessment. Velocity will also vary

between the flow surface and base, and from bank to bank. Velocity across and within a channel may present a gradient from zero at the sides and base to a maximum at the channel center and surface. Thus, the spatial point at which the velocity measurement is made must be noted so that it can be related to the maximum and mean velocity (see later), both in terms of position across a channel, as well as down system.

2 Parameters to be Measured

2.1 Mapping Spatial Extent and Dimensions

Monitoring lava flows starts with acquiring the geographic coordinates of the eruption site. This requires location on the Global Navigation Satellite System (GNSS) for the ends of the eruptive fissures and thus also their length and strike, or point location of single vent. The flow front position is next most important point to locate, and hence the flow length at time t . The evolving length should then be tracked. Ideally flow outline and thickness should be obtained too, and terrain and topography updated so as to allow the trajectory of any new flow to be assessed.

Fissure or vent location can be obtained by hiking to the eruption site with handheld GNSS. However, lava flows often occur in remote places, and it is often difficult, or impossible to get close to the vent. In this case, airborne surveys are the most efficient manner to obtain the required coordinates with a handheld GNSS. Since the 1980's, reconnaissance overflights have been mainly operated using helicopters. Satellite images are also consulted to detect the associated hotspot and may rapidly provide an approximation of localization of the lava flow extent although at low resolution (1–4 km/pixel), or better if there is an overpass by a satellite with higher (30–60 m/pixel) spatial resolution (see chapter Monitoring Heat). Other options for an approximation of the eruptive

vent are location are through tracking the tremor sources or use of webcam networks.

During an eruption, the extent of an expanding flow can be tracked in multiple ways, depending on the flow setting and dimensions. Ground-based mapping can be carried out by walking the flow limits with a handheld differential GNSS, using webcam networks or by UAS. UAS-derived images can be stitched together to construct georeferenced orthomosaics from which the flow outline can be derived. Additionally, UAS images can be used for photogrammetry by applying structure from motion (SfM) technique to reconstruct the 3D topography and to produce an updated DEM. Over the past decade, this technique has become common. UAS-based surveys are ideal for areas of less than 1 km², so as to map parts of the flow, local features, vent areas, breakouts and flow fronts. However, flow-field-wide orthomosaics and DEMs exceeding a few km² need airborne surveys to be carried out by ultralight aircraft or helicopters (Fig. 3).

In Hawaii, helicopter overflights were carried out every week, and sometimes daily, during the last recent effusive crisis of 2018. Images acquired by a handheld thermal camera from an airborne survey were used for mapping (Patrick et al. 2017). Airborne Light Detection and Ranging (LiDAR) surveys can also be conducted to allow millimeter topographic precision, though coverage is usually local and costs are high. At Piton de la Fournaise (La Réunion), lava flow field evolution is usually mapped via ultralight aircraft surveys, which have a more reasonable price (Fig. 3).

Satellite imagery is the most efficient way to track the evolution of a lava flow field and to capture the entire lava flow field within a single image. Satellite thermal and visible imagery (see chapter Monitoring Heat) have spatial resolutions of 15–60 m (TM, ETM+, ALI, ASTER), and down to a meter for Planet Labs products, and to sub-meter for the GeoEye and WorldView satellites, for example (as used by Google Earth). In case of cloud

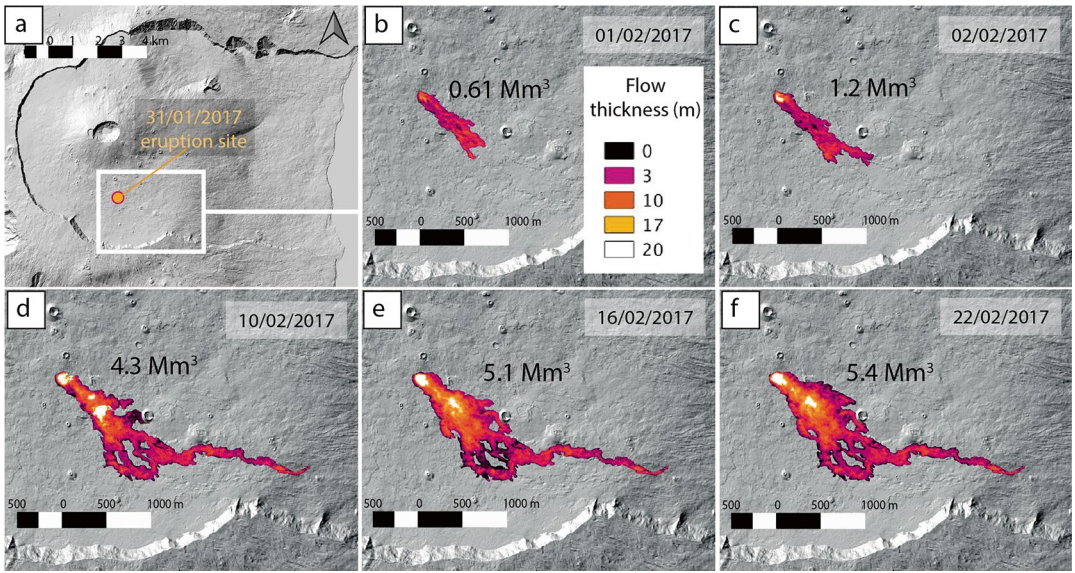


Fig. 3 **a** Location of the eruptive site of the 31 January—27 February 2017 eruption of Piton de la Fournaise volcano, La Réunion. **b–f** evolution of the

flow area, thickness (in m) and corresponding volume (in Mm^3) has obtained from repeat photogrammetric campaigns. Figure from Derrien (2019)

coverage satellites equipped with radar sensors can be used to monitor ground surface displacement through Interferometry Synthetic Aperture Radar (InSAR) (e.g., ERS, Envisat, TerraSAR-X, Sentinel 1, ALOS-2). InSAR also allows the newly emplaced lava flow to be identified by comparing an image before and after lava flow emplacement, because emplacement of the new flow results in a highly incoherent

are (low coherence, Fig. 4). Coherence maps can therefore be used to define the lava flow outlines under any weather conditions (Bato et al. 2016; Dieterich et al. 2012; Harris et al. 2019; Poland 2022).

An example of a recent advance in mapping from satellite imagery are the activities of the Copernicus Emergency Management Service (2022; <https://emergency.copernicus.eu/>). Since

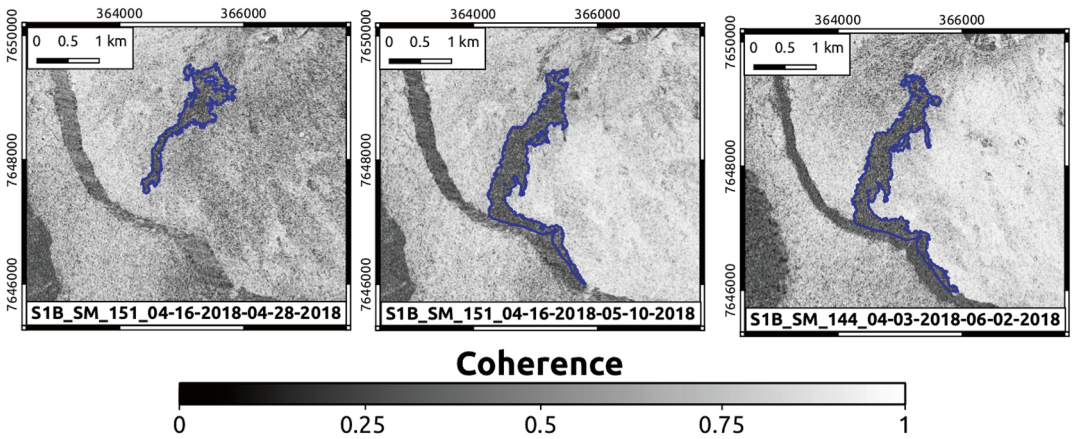


Fig. 4 Evolution of the flow outlines and extension of the lava flow field as mapped from InSAR coherence maps obtained via the Oi² platform ([https://opgc.uca.fr/](https://opgc.uca.fr/volcanologie/oi2)

[volcanologie/oi2](https://opgc.uca.fr/volcanologie/oi2)) during the April 2018 eruption of Piton de la Fournaise (modified from Harris et al. 2019)



A thermocouple is required to obtain temperature of flow interior. Interior temperature is typically hundreds of degrees centigrade higher than

1. Probes are typically less than a meter long (e.g., Fig. 6). The measurement thus requires close approach to the active lava, which will have surface temperatures greater than 800 °C, and an interior at up to more than 1100 °C. This can be at best uncomfortable and at worst painful, and means that all exposed flesh needs to be well covered to avoid radiation burns. Approach, if possible, should also be made up-wind, which is especially true at skylights where heated air blowing out of the tube system can have temperatures >600

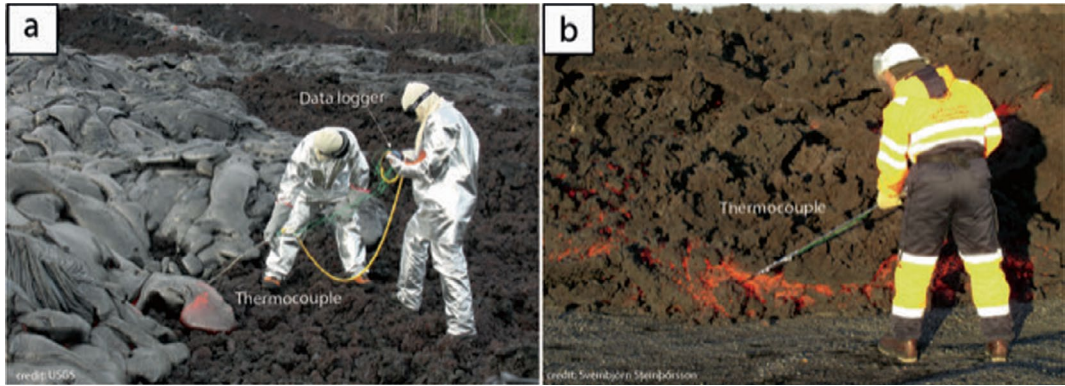


Fig. 6 Measuring lava temperature at **a** pāhoehoe lava lobe with k-type thermocouple that is 60 cm long with a 3 mm thick sheath and linked to a data logger (Hawaii 2016; photo: © USGS, M. Patrick) and **b** at an ‘ā’ā

flow front using thermocouples mounted on a steel pole deeply inserted into freshly exposed lava (Holuhraun, Iceland 2014; Kolzenburg et al. 2017)

- °C. A fire suit and helmet is one solution (Fig. 6), and metal shield can be used to block the radiation emitted by the lava surface. A longer probe could be another solution, but as they become longer than 1 m they tend to bend upon insertion, making penetration difficult. In such a case, the probe can be attached to a rigid steel pole to ease penetration through the crust.
2. To protect the delicate wires, a metal sheath is used. This needs to be at-least 3 mm thick. Such a thickness is required to allow the probe to penetrate the surface crust. However, the sheath needs time to heat up which means that the reading will pick up over a period of one to two minutes. Once the reading is stable the measurement is made. This means that the operator needs to stay in-situ for the same amount of time.
 3. Due to lava quenching to the probe, the sensor may not heat to the same temperature as the surrounding lava. In such a case, the reading will begin to decline without stabilizing and the probe should be withdrawn. It is thus best to (i) have a pre-measurement idea of what the maximum temperature should be, and (ii) continue to make the measurements until you have at-least three that are the same and stable.
 4. Care should be taken not to ground the probe on the cooler flow base, and to ensure that

the probe is well within the fluid interior and not in the cooler visco-elastic crust. Finally, you should constantly stir to (i) avoid lava quenching to the probe, and (ii) avoid the probe becoming entrapped in the constantly forming surface crust.

5. If the flow is too large, close approach will not be possible due to the radiative heat and/or the measurable zones being inaccessible in a sea of hot, recently emplaced lava. Also, flow margins may be too unstable to allow safe approach and/or flow surface in a channel may be too far below the levee rim. The easiest targets to measure are small pāhoehoe lobes (Fig. 6a), or slowly moving breakouts through lava fronts or margins (Fig. 6b), but these are not always available or accessible.

Remember, that upon completion of the measurement the metal sheath of the thermocouple will remain extremely hot for several minutes, so on no account touch it. Also, after each measurement, the lava attached to the probe will need to be quenched in water and then broken off with a hammer.

2.2.2 A First Idea of the Surface Temperature

The simplest way to gain a ball-park estimation of lava surface temperature is visually by matching surface color to the temperature associated

with that color. This best done at night and is the principle of the optical pyrometer. The pyrometer consists of a heated wire, the temperature of which is adjusted to change the color at which it glows. When viewed against active lava, the point at which the color of the wire is not distinguishable from the surface in the background gives the temperature of that background. Alternatively, the assessment can be made visually and a lookup table used to assess the temperature (Harris 2013).

2.2.3 Thermal Infrared Thermometer (Surface Temperature)

The thermal infrared thermometer uses radiated heat to obtain surface temperature and usually works with spectral radiant exitance in the 8–14 μm range. Note that, given the high temperature range of active lava surfaces, a model which can measure the full range of expected temperatures from ambient out to 1200 $^{\circ}\text{C}$ needs to be used. Being a remotely sensed measurement, no close approach is necessary. However, the measurement is of a radiative temperature (T_{rad}) and will not be the kinetic temperature of the surface. That is, most bodies are not perfectly emitting blackbodies, so that spectral radiant exitance from a surface emitting at kinetic temperature T_{kin} and wavelength λ will be reduced by a factor described by the emissivity (ϵ). Spectral radiant exitance, $M(\lambda, T)$, varies as a function of wavelength and temperature (T), and is given by the Planck function:

$$M(\lambda, T) = c_1 \lambda^{-5} \left[\exp \frac{c_2}{\lambda T} - 1 \right]^{-1} \quad (1)$$

Here c_1 and c_2 are constants with the values of $3.741 \times 10^{-16} \text{ W m}^2$ and $1.4393 \times 10^{-2} \text{ m K}$, respectively. Note that units of wavelength and temperature thus need to be in units of meters and Kelvin, and $M(\lambda, T)$ has the units W m^{-2} , i.e., $\text{J s}^{-1} \text{ m}^{-2}$.

Equation (1) applies to a black body, however for a body with an emissivity less than one the function becomes:

$$M(\lambda, T_{\text{rad}}) = \epsilon M(\lambda, T_{\text{kin}}) = \epsilon c_1 \lambda^{-5} \left[\exp \frac{c_2}{\lambda T} - 1 \right]^{-1} \quad (2)$$

Thus, to obtain the actual surface temperature, we need to convert the radiative temperature to a spectral exitance using Eq. (1), divide the value of $M(\lambda, T)$ by emissivity, and convert the result back to temperature, which will now be a kinetic temperature. This can be done by inverting the Planck function:

$$T_{\text{kin}} = \frac{c_2}{\lambda \ln \left(\frac{\epsilon c_1 \lambda^{-5}}{M(\lambda, T_{\text{rad}})} + 1 \right)} \quad (3)$$

Emissivity will vary with wavelength and surface type, where those for typical lava surface types are given in Table 1. There is debate over what the emissivity for a molten surface should be, and there is evidence that emissivity changes with temperature and composition (Biren et al. 2022; Burgi et al. 2002), but the values of Table 1 are those typically used.

The measured surface temperature will not be that of the interior. Rapid radiative cooling means that the surface temperature can cool by 50–300 $^{\circ}\text{C}$ within a second of exposure.

Table 1 Band-averaged emissivity values for a range of lava flow types (from Harris 2013). Note that these are values for cold sample, and not molten material

Location	Type	Emissivity 8–14 μm
Kilauea	Basalt: pāhoehoe	0.901
Kilauea	Basalt: ‘ā’ā	0.954
Kilauea	Basalt: pāhoehoe—ropey	0.943
Kilauea	Basalt: pāhoehoe—smooth, glassy	0.900
Kilauea	Basalt: pāhoehoe—vesicular	0.909
Etna	Basalt: pāhoehoe—slabby (spiny)	0.957
Etna	Basalt: ‘ā’ā	0.971

spot temperature. Focal plane arrays tend to comprise 640×480 pixels, with each pixel having an instantaneous field of view (IFOV) of 0.65 mrad and the image having a total field of view (TFOV) of $24 \times 18^\circ$ up to $45 \times 12^\circ$. For a perfectly horizontal or vertical field of view the pixel or image diameter field of view (D_{FOV}) can be calculated using the simple trigonometric relation:

$$D_{\text{FOV}} = 2[D \tan(\beta/2)] \quad (4)$$

where D is the distance to the pixel or image center and β is the angular IFOV or TFOV. If the ground within the field of view is sloping, then D_{FOV} should be corrected for slope (α):

$$D_{\text{FOV}}(\text{slope corrected}) = D_{\text{FOV}}/\cos(\alpha) \quad (5)$$

For oblique viewing angles the viewing angle (θ) needs to be taken into account (Fig. 8). For a viewing position h meters above the surface, this can be achieved using:

$$D_{\text{FOV}} = h \left[\tan\left(\theta + \frac{\beta}{2}\right) - \tan\left(\theta - \frac{\beta}{2}\right) \right] \quad (6)$$

For a viewing position x meters away from the surface (Fig. 8), calculation of D_{FOV} requires replacing h with x in Eq. (6).

Pixel temperatures will be subject to the same emissivity correction as described for the thermal infrared camera, but also (for distances greater than 100 m) requires atmospheric correction. The signal received by the camera will be a mixture of the surface emitted radiant exitance, $\epsilon M(\lambda, T)$, as well as that emitted by the atmosphere, termed atmospheric upwelling radiance (M_U). This will all be modified by atmospheric absorption (ψ) as described by transmissivity ($\tau = 1 - \psi$). Thus, the temperature recorded by the camera is a brightness temperature (T^*) given by (Fig. 9):

$$M(\lambda, T^*) = \tau(\lambda)\epsilon(\lambda)M(\lambda, T_{\text{kin}}) + M_U(\lambda) \quad (7)$$

Atmospheric correction thus needs to take into account the emissive and absorptive properties of the atmosphere. This can be done by rearranging Eq. (7) so that,

$$M(\lambda, T_{\text{kin}}) = [M(\lambda, T^*) - M_U(\lambda)] / [\tau(\lambda)\epsilon(\lambda)] \quad (8)$$

The atmospheric properties will vary with altitude and distance. The atmosphere becomes thinner with increased altitude and decreased path length, so that M_U and τ decrease accordingly. Typical correction values, as a function of altitude and distance are given in Fig. 9.

Thermal camera measurement principles are the same whether the measurement is made from the ground or an aircraft. For airborne measurements the craft needs to fly sufficiently slowly so as to avoid image smearing, and doors must be off otherwise the temperature of the glass, which is 100% opaque in the infrared, will be recorded. However, for both cases to solve the relations given above the acquisition conditions need to be recorded, as given in Fig. 10.

2.2.5 A Short Note on Temperature Retrievals from Satellite-Based Sensors

Satellite-based sensors operating in the thermal infrared (typically $10\text{--}14\ \mu\text{m}$), as well as in the mid (typically $3.5\text{--}4.0\ \mu\text{m}$) and short-wave (around $2.5\ \mu\text{m}$) infrared, can provide temperature information. However, these are pixel-integrated temperatures meaning that the measurement is an integration of all surfaces emitting within the pixel, which is typically 30 to 4000 m in dimension. Mixture modelling can retrieve this surface structure, but are subject to the need to oversimplify a complex problem. That is, a continuum of temperatures between background (ambient) and eruptive (ca. 1200°C) need to be described by a mixture model with, typically, two components (hot and cold). Such mixture models are also blighted by issues of saturation, where instrument gain settings were not designed for measurements over high temperature surfaces. Instead, the maximum temperature that can be recorded in the thermal infrared is typically $60\text{--}120^\circ\text{C}$, and in the shortwave around 250°C . Thus, over active lavas, all pixels are saturated with the only information available being that the temperature is

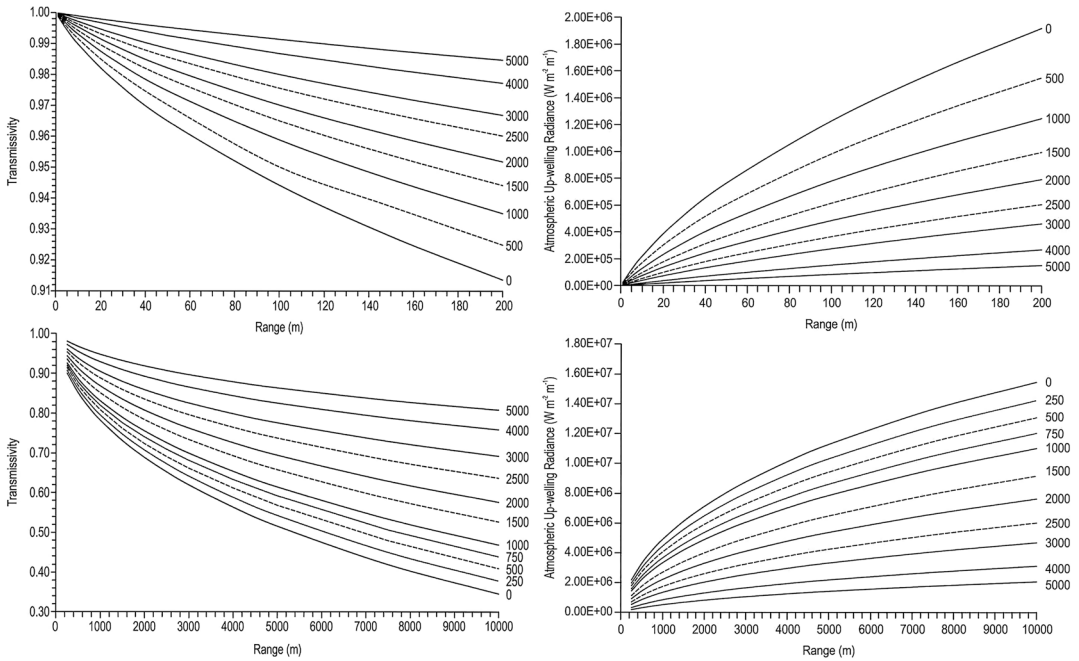


Fig. 9 Increase in atmospheric transmissivity (left graphs) and upwelling radiance (right graphs) for a horizontal line of sight (LOS) at a range of altitudes between 0 to 10 000 m (top graphs are a zoom on the 0 to 200 m range). Values were obtained using MODTRAN with 1976 US Standard atmosphere and a CO₂ mixing ratio of 380 ppm-v across the 7.5 μ m to 13 μ m waveband and are from (Harris 2013). Note that, after a distance of only 10 m transmissivity begins to become an issue, with almost 6% of the signal being absorbed by a distance of

100 m at sea-level. At ambient temperatures, upwelling radiance is an issue, accounting for 20% of the signal received by an infrared detector placed at a distance of 1 km from a surface at 0 °C. However, for higher temperatures the contribution is not so important, being 3% for surfaces at 200 °C and 1% for surfaces at 500 °C (see Harris 2013). Thus, at higher temperatures the correction for upwelling could be ignored for an approximation of kinetic temperature, but transmissivity cannot

greater than saturation. Worse, the point spread function and optical reflection can cause intense smearing in the imagery and halo effects. Thus, satellite-based sensors are not, currently, well suited for retrieval of absolute temperature, but can be used for mapping (See Chapter Monitoring Heat for More Details).

2.3 Lava Surface Velocity

Surface velocity can be obtained from a series of images (or video) collected in the field or from the air using a camera and particle velocimetry. This consists of tracking a particle, or a set of particles, on scaled digital photos or thermal images acquired at a known frequency. Velocity is then calculated from the distance

travelled by the particle and the time between two images, plus the vector. For this, pixel size must be well known and calculated according to distance from the target and IFOV following the trigonometric relations as described in the in Sect. 2.2.4. In case of images or video footage acquired via UAS, a nadir view is ideal as obtained with a stationary hover and a FOV covering the whole channel including the stationary levée to anchor the velocity, with a few minutes of recording being ideal (James et al. 2020). Particle velocimetry software, such as PIVlab (Thielicke and Stamhuis 2014), can be used to analyze a few minutes of video. Output may then be used to derive velocity profile over the full width and depth of a channel (e.g., Bailey et al. 2006; Harris et al. 2007a, b; 2019; Dietterich et al. 2021), and integrated over

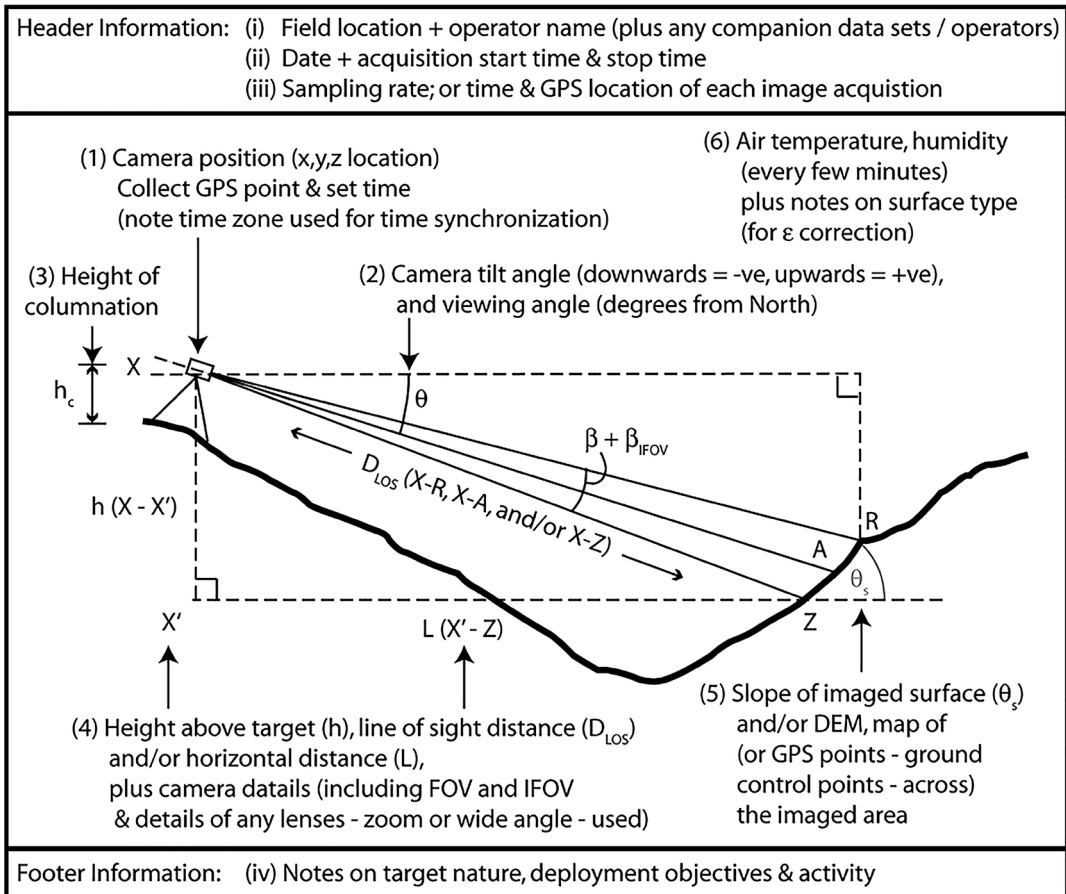


Fig. 10 Parameters to be recorded in a field note book at the time of image acquisition to allow adequate geometric and atmospheric correction of a thermal image.

DEM: Digital Elevation Model, GPS: Global Positioning System, (I) FOV: (Instantaneous) Field of View, LOS: Line of sight. From (Harris 2013)

channel width and depth to estimate IER and its local fluctuation (see Sect. 3).

2.4 Sampling

Collecting rock samples during an eruption has the main objective of providing time-series for the physio-chemical properties of the magma so as to provide insights into the eruption source and allow initialization of lava flow simulation models (Harris et al. 2017, 2019). Following the evolution of texture, chemical composition and petrology during an eruption has come to be known as petrological monitoring and involves

collection and distribution of data as soon as samples have been received, prepared and analyzed (e.g., Gurioli et al. 2018; Pankhurst et al. 2022; Gansecki et al. 2019).

Effective petrological monitoring involves sampling volcanic deposits as soon as, and as often as, possible during an ongoing eruption because the emitted lava may be buried the next day by a new flow or fallout. The main problem with sampling an active lava flow is access. Lava channels and tubes are often inaccessible, and recently emplaced and hot lava usually needs to be crossed to access the flow. Where accessible, sampling of molten lava has to be carried out with appropriate protective clothing and sampling tools (Fig. 11).

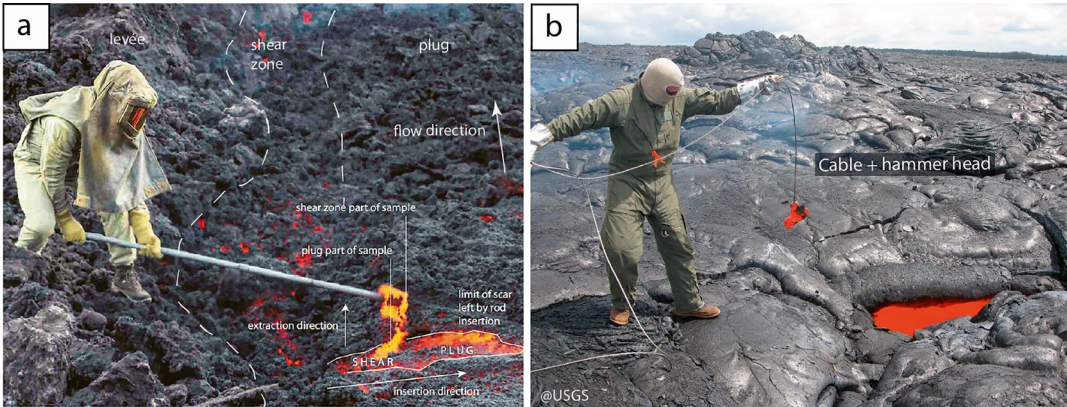


Fig. 11 **a** Sampling a lava channel from a stable *levée* (Piton de la Fournaise, La Réunion 2015; Harris et al. 2020); a heat suit and 2-m stainless steel pole welded to a scoop was used operators. **b** Sampling a lava tube

through a skylight (Kilauea, Hawaii 2010) (courtesy of USGS Hawaiian Volcano Observatory); here a hammer head on a cable is being used, and the operator has a fire-resistant balaclava and flight suit

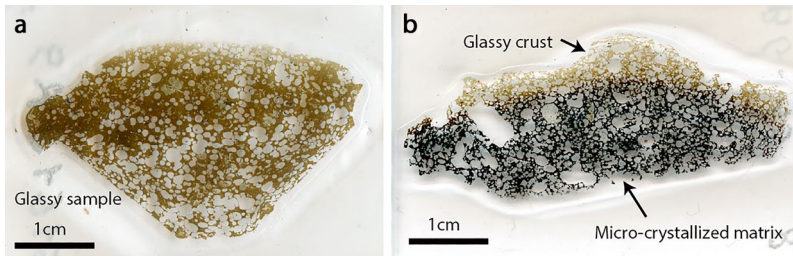


Fig. 12 Polished thin sections of basaltic lava collected at Kilauea (Hawaii) in 2016. **a** Lava sampled with a stainless-steel rod and quenched in water. The sample is entirely glassy and preserves crystal and bubble size

distributions. **b** Naturally cooled sample of the same lava showing a glassy crust (brown) and a non-glassy micro-crystallized interior (black)

Samples of molten lava must be rapidly quenched in water, which will freeze-in the lava physico-chemical and textural properties before any modifications due to a slow cooling (which cause micro-crystallization, element diffusivity, post-sampling vesiculation and expansion). Such a sampling method ensures retrieval of the proportion of phases, glass composition and redox state (Fig. 12), and requires the following to be carried to the sampling site:

1. Sampling instruments (hammer, chain, shovel ...);
2. Several liters of water for quenching;
3. A container to quench the sample in.

Waiting for the sample to cool in air will result in complete crystallization of the groundmass as well as re-organization of the vesicle population. The resulting interstitial melt phase will therefore not be glassy and representative of the flow state, but instead will display a microcrystalline groundmass typical of slow, in-situ (post-emplacement) cooling (Fig. 12). This means that the microlite and bubble contents present during flow will be overprinted and lost. If the surface layer is naturally quenched so as to preserve a thin glassy rind, then this layer can be representative of the molten lava (Fig. 12b). However, such layers are hard to find but allow down flow cooling to be obtained from the glass chemistry

(e.g. Robert et al. 2014; Chevrel et al. 2018a). Sample must be taken ‘in-place’; meaning it is not a rafted fragment that was quenched closer to the vent and then transported down flow.

2.5 Lava Flow Morphology/ Typology

Lava flow type and associated morphology should be reported as it gives indication on lava flow dynamics. Field book entries for the day should include descriptions and sketches of:

1. The lava flow distribution system (channel, tube-fed, dispersed ...);
2. Lava flow type (juvenile ‘ā’a, mature ‘ā’a, blocky, transitional, s-type/p-type pāhoehoe);
3. Flow field form (ridged, ogives, ramped, ropey, hummocky, sheet ...);
4. Any associated features (skylights, lava balls, lava boats, tumuli, shatter rings ...).

Included for each entry should be estimates of approximate dimensions, especially length, width, height and depth of any feature, as well as underlying and new surface slope (Fig. 13). Of course, titles, orientations, scales, dates, times, GNSS points and tags for photos taken should be entered.

3 First Order Derivatives

3.1 Building DEMs and Volume Estimation

To assess lava flow paths, the changing topography during an eruption needs to be constantly updated. DEMs are typically constructed through stereophotogrammetry. This involves merging georeferenced images taken from different angles. Images are either acquired by UAS (James et al. 2020), during flight surveys (Derrien 2019) or from satellite sensors operating in the visible (Bagnardi et al. 2016). To build a DEM either multiple ground control points

(GCPs) are used to allow scaling and georeferencing (the larger the study area, the more GCPs are required) or, as usually applied during an eruption, images are geotagged to allow georeferencing. During an eruption establishment ground markers on foot is often impossible. Data processing then involves applying SfM using software such as Pix4D, Metashape or MicMac. Space agency services also produce DEMs from optical data (e.g., ASTER GDEM), from multi-view optical systems of high spatial resolution (e.g., tri-stereo Pleiades), or from radar data (e.g., SRTM and tanDEM-X; Zink et al. 2014).

LiDAR involves a pulsed laser that returns three-dimensional information of the targeted surface. After filtering, retrieved point clouds allows generation of the topography. LiDAR may either be mounted on an airplane or on an UAS, and provides very high-spatial resolution DEMs (of a few cm), although at high cost (Cashman et al. 2013).

Reconstruction of the new topography has two main goals. First, if topography is obtained rapidly and regularly it can be used to update and improve numerical simulations of lava flow paths. Second, the new DEM can be used to quantify the lava flow field volume (see above).

3.2 Velocity Profile and Spreading Rate

In the field, as well as in thermal and visible video, flow velocities can be obtained by timing the transit time of a marker, such as a piece of crust, over a known distance (Sect. 2.2.4).

3.2.1 Velocity Profiles

For surface measurements, velocity will increase from a minimum at the channel margins to a maximum ($v_{\max}$) towards the center. The reverse will reply with depth where velocity will decrease from a maximum at the surface to a minimum at the flow base (Fig. 14). It is thus important to place the measurement in terms of where it is taken within this velocity profile,

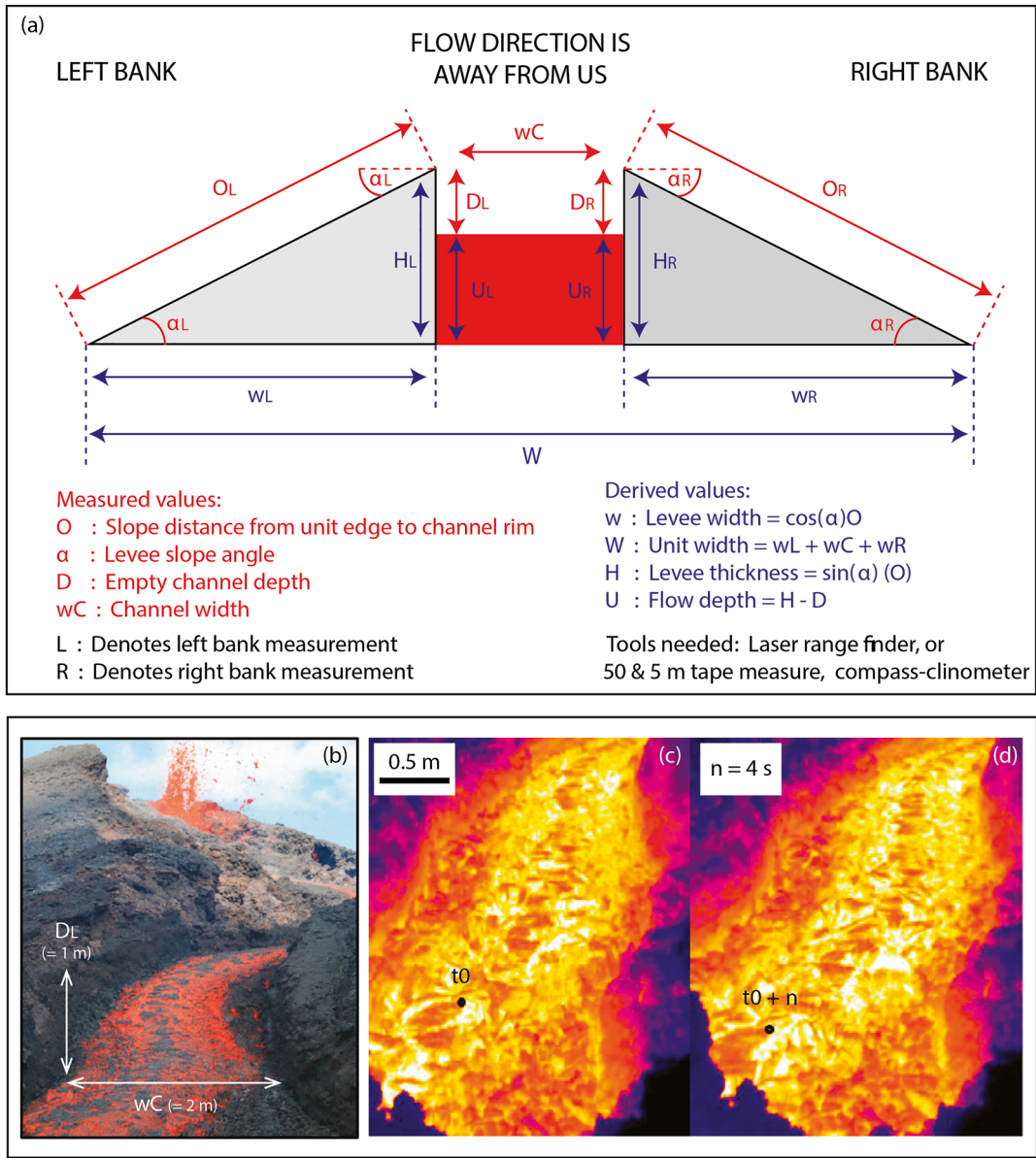


Fig. 13 **a** Channel dimensions to be measured and calculated (from Harris et al. 2022), with **b** example of below bank flow from a channel active at Piton de La Fournaise (La Réunion) on 1 August 2015 (modified from Harris et al. 2020). Dimensions were obtained from scaled digital photos and thermal images. Thermal images were collected at a frequency of 4 s. In **c** a piece

of cooler crust has been selected as close to the channel center as possible, and found again in the next image obtained, as given in **d**. The object has travelled 0.2 m in 4 s, so velocity is 0.05 m/s. Given the channel width and a square channel that is as wide as it is deep gives an effusion rate of $[2 \text{ m} \times 2 \text{ m} \times (0.67 \times 0.05 \text{ m/s})] = 0.13 \text{ m}^3/\text{s}$

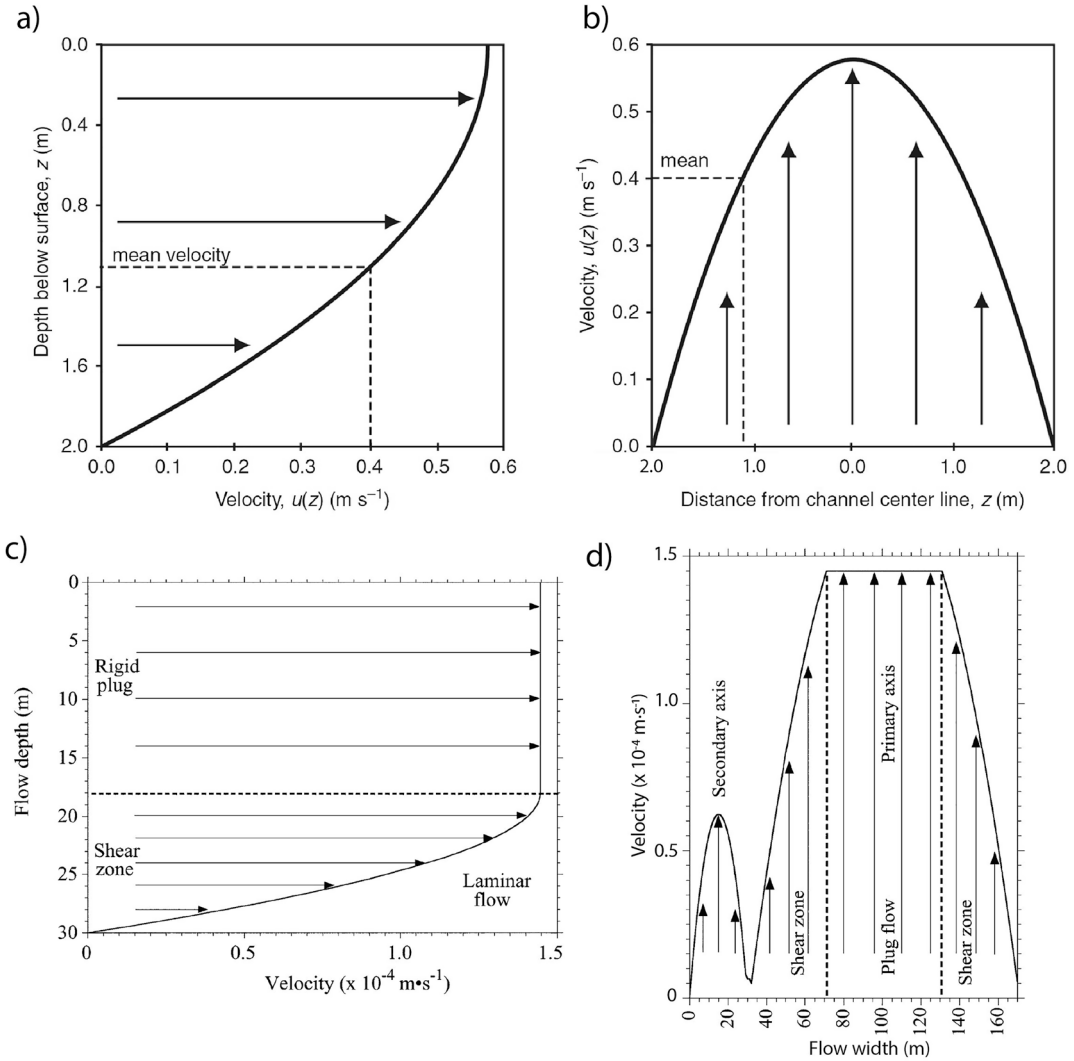


Fig. 14 Vertical **a** and horizontal **b** velocity profiles for Newtonian flow (Etna, Italy 2001, from Bailey et al. 2006), and for Bingham flow **c** and **d** (Santiago, Guatemala 2001, from Harris et al. 2002)

where the safest approach is to take the maximum value at the channel center.

For wide channel and assuming a Newtonian rheology, the velocity profile can be calculated for a channel of width or depth h from the Jeffreys' (1925) equation:

$$v(z) = \frac{\rho g \sin(\alpha)(h^2 - z^2)}{n\eta} \quad (9)$$

Here, ρ is density, g is gravity, α is slope, n is a constant equal to 3 for wide channel (i.e., much

wider than deeper), to 4 for narrower channel and to 8 for semi-circular channels and η is viscosity, and the coordinate system is:

$z=0$ at the channel center and/or surface (where $v(z)=v_{\max}$), and,

$z=h$ at the channel margins and/or base (where $v(z)=0$).

Average velocity is typically $2/3 \times v_{\max}$ (Fig. 14a) and can be calculated from,

$$v_{mean} = \frac{\rho g \sin(\alpha) h^2}{n\eta} \quad (10)$$

Thus, an important measurement to help constrain the velocity system is flow width and, if possible, depth. Another important piece of information is whether there is a plug, or zone of non-sheared lava, at the channel center. Across this plug all flow is at the same velocity, so that the velocity profile needs be calculated with the limits of:

$z=0$ at the plug edge and/or base (where $v(z)=v_{max}$), and
 $z=h$ at the channel margins and/or base (where $v(z)=0$),

as applied in (Fig. 14c).

Mean velocity can be calculated to take into account yield strength (i.e., Bingham rheology), rather than Newtonian, fluid using (Moore 1987):

$$v_{mean} = \left(\frac{\rho g \sin(\alpha) h^2}{n\eta} \right) \left(1 - \frac{4}{3} \frac{\tau_0}{\tau} + \frac{1}{3} \left(\frac{\tau_0}{\tau} \right)^4 \right) \quad (11)$$

Here, τ_0 is yield strength, which can be calculated from plug width (w_p), where $\tau_0 = w_p \rho g \sin(\alpha)$, and τ is the basal shear stress [$\tau = \rho g h \sin(\alpha)$].

3.2.2 Spreading Rate

If pixel dimension is known, feature width, length, perimeter and area (A) can be measured from airborne thermal imagery. Changes from overflight-to-overflight can then be used to derive advance velocities and spreading rates. Application of thermal chronometry can also be used to estimate the time since emplacement (t) (Harris et al. 2007b). This is based on the characteristic cooling that the flow surface experiences and which can be empirically described by (Hon et al. 1994):

$$T_{surf} = -140 \log(t) + 303 \quad (12)$$

where t is time since emplacement in hours. Now the surface temperature can be used to derived age from:

$$t = 146 \exp(-0.0164 T_{surf}) \quad (13)$$

Lava area emplaced over given periods can now be mapped, and the area (ΔA) and time (Δt) differential used to obtain spreading rate ($\Delta A/\Delta t$) (Fig. 15).

3.3 Heat Loss and Cooling Rate

The two main heat losses from a lava flow surface are due to radiation (Q_{rad}) and convection of the air above the lava surface (Q_{conv}). In terms of heat flux density ($W m^{-2}$) these can be written:

$$Q_{rad} = \varepsilon \sigma (T_{surf}^4 - T_{amb}^4) \quad (14a)$$

$$Q_{conv} = h_c (T_{surf} - T_{amb}) \quad (14a)$$

Here, σ is the Stefan Boltzmann constant ($5.67 \times 10^{-8} W m^{-2} K^{-4}$), T_{surf} is the ambient temperature (in Kelvin), and h_c is the convective heat transfer coefficient ($35-50 W m^{-2} K^{-1}$). If flow depth (t) and mean velocity (v_{mean}) have also been measured, we can also estimate the heat flux density supplied from advection (Q_{adv}) and generated by crystallization (Q_{cryst}) from:

$$Q_{adv} = v_{mean} t \rho c_p (dT/dx) \quad (15a)$$

$$Q_{cryst} = v_{mean} t \rho C_L (d\phi/dT) (dT/dx), \quad (15b)$$

in which c_p is lava specific heat capacity, dT/dx is cooling rate per unit distance, C_L is latent heat of crystallization, and $d\phi/dT$ is fraction crystallized per degree cooling. This can be solved if $d\phi/dT$ and/or dT/dx have been measured through sampling and/or thermocouple measurements at different down flow points. On the other hand, if $d\phi/dT$ can be assumed, then cooling rate can be estimated.

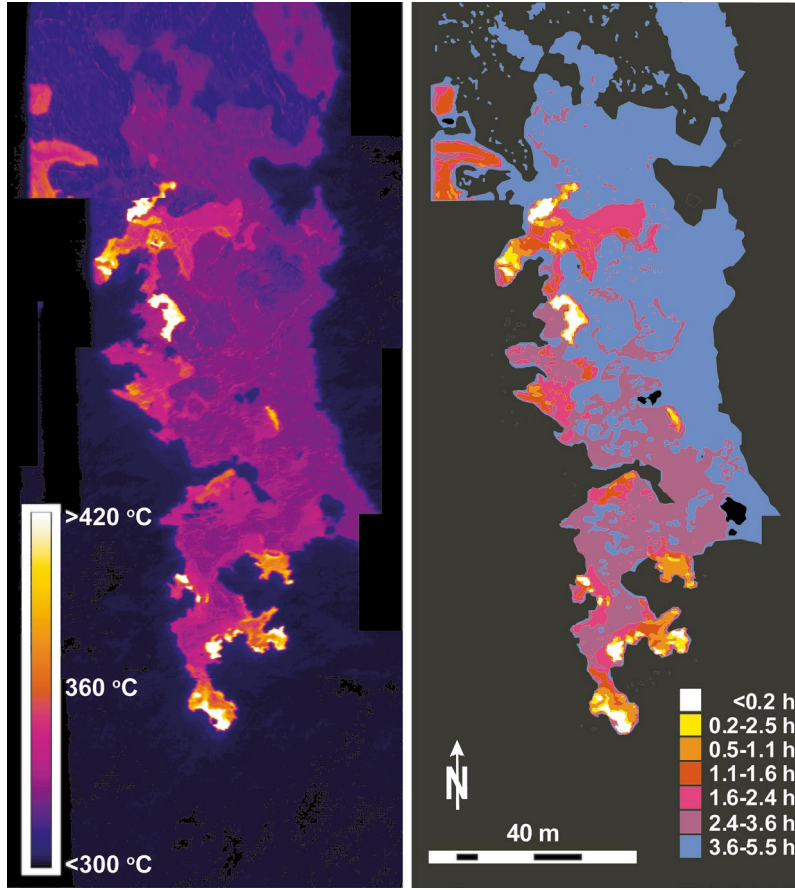


Fig. 15 Surface temperature and conversion to time since emplacement for a pāhoehoe flow active on Kilauea (Hawaii) in 2006. This is a mosaic of five images acquired vertically from a helicopter hovering

200 m above the surface. An area of 2400 m² was covered in the 1.1 h prior to acquisition to give a spreading rate of 2180 m² per hour. From (Harris et al. 2007a, b)

Here, we have a system whereby heat is supplied by Q_{adv} and Q_{cryst} , and lost by Q_{rad} and Q_{conv} . In our case, the heat lost is not balanced by heat supplied, i.e.,

$$Q_{rad} + Q_{conv} > Q_{adv} + Q_{cryst} \quad (16a)$$

As a result, the system is in disequilibrium and cools as a response. Given this imbalance, if we write the condition of 16a out in full and rearrange to isolate cooling, we arrive at:

$$\frac{dT}{dx} = \frac{Q_{rad} + Q_{conv}}{v_{mean} t \rho \left(c_p + c_L \frac{d\phi}{dT} \right)} \quad (16b)$$

This approximation can be used to estimate potential flow length of a cooling-limited lava flow (cf. Harris and Rowland 2001). For example, if the cooling rate is 10 °C per kilometer, and the difference between eruption temperature and solidus, or the point at which the flow can

no longer move is 300 °C, then the maximum likely cooling-limited run out is 30 km. This back of the envelop calculation is very much an approximation, but can give a first order idea as to likely flow run out.

3.4 Sample Chemical Composition and Texture

Analyzing rocks take time because samples need to be cut, powdered and polished thin sections produced. For a long time, sample analyses were therefore only used for research purposes. However, over the last decade, analytical analyses have become faster and more sophisticated petrological monitoring has now becoming more efficient (Gurioli et al. 2018; Re et al. 2021). Early petrological monitoring of effusive activity at Kilauea by HVO during the 1980s and 1990s contributed to assessing the state of the magmatic system feeding effusion (e.g. Thornber et al. 2003). Analyzes also allowed tracking of eruption temperatures and cooling rates through application of glass geothermometry (e.g., Helz et al. 2003).

More recently, the response system of DYNVOLC (<http://dx.doi.org/https://doi.org/10.25519/DYNVOLC-Database>) allows timely petrological and textural monitoring (Gurioli et al. 2018). As part of DYNVOLC, analyses are completed as soon as sample has been delivered during any eruption of Piton de la Fournaise (La Réunion) to contribute to monitoring efforts by the observatory (Harris et al. 2017). This response system was also applied recently during the submarine eruption offshore of Mayotte where Berthod et al. (2021) performed detailed petrographic analyses of collected submarine samples to contribute to monitoring efforts. Another recent example is Pankhurst et al. (2022) who published a report on the rapid petrological monitoring response to the La Palma eruption of 2021 where petrographic and geochemical analyses conducted within 10 days of sampling.

Petrological monitoring is therefore a key action to best constrain and understand an ongoing effusive event. The first information to obtain is bulk rock chemistry, including major and trace elements. Major element composition is essential for rock type classification and to assess physical properties of the magma and lava, such as density and viscosity, essential for lava flow modeling. Trace elements, inform on magma storage conditions and ascent, and evolution of these conditions through time. This information is essential to track any changes of magma properties and to track whether there is a new magma recharge, or an evolution toward more silica-rich or volatile-rich composition that could force the eruption to transition toward explosive behavior (cf. Coppola et al. 2017).

As part of the petrological monitoring approach, bulk and glass chemistry analyses are supported by detailed descriptions of sample petrology and texture. Petrological analyses give information on the magmatic plumbing system including magma source depth, residence time, ascent rates, and ascent path. Magma reservoir depth (pressure) and temperature are essentially obtained through thermobarometry (see Putirka, (2008) for review). Crystal size distribution, crystal donation, reaction rim features are also used to constrain ascent rate and path (e.g. Rutherford and Hill 1993). Textural analysis includes consideration of density, porosity, percentage of crystals and vesicles, as well as, crystal and bubble size distributions. The derivatives inform on the ascent dynamics, especially for explosive phases because the texture is preserved at magma fragmentation (e.g., Rust and Cashman 2011; Gurioli et al. 2008). In the case of monitoring lava flows, sample analysis provides information on lava temperature (using geothermometry), cooling rate, crystallization history, phase (melt, crystal, bubble) proportion, redox state and, hence, flow thermo-rheological properties (e.g., Guilbaud et al. 2007; Harris et al. 2020; Robert et al. 2014; Chevrel et al. 2018a).

When monitoring a lava flow, to allow the lava rheological state to be assessed, it is essential to:

1. measure the bulk rock and glass major element composition and volatile content,
2. estimate the temperature at the eruptive vent and then down flow to constrain cooling rate,
3. measure density including dense rock equivalent and derive porosity,
4. estimate the vesicle and
5. estimate the crystal (phenocrysts and micro-lite) contents and size distribution.

4 Second Order Derivatives

4.1 Volume Flux

4.1.1 Instantaneous Effusion Rate from Lava Velocity

Effusion rate (E_r) is given in m^3/s and defined as (Sect. 1.3.2):

$$E_r = v d w \quad (17)$$

in which v , d and w are flow velocity, depth and width, respectively. The “simplest” way to calculate this is by measuring v , d and w in the field at an active channel or tube (via a view through a skylight).

Velocity can be estimated using the time needed for a surface marker, such as a distinctive piece of crust, to move across a known distance (Sect. 2.2.4). Because velocity will vary across the channel (see Fig. 14), care must be taken to make this measurement at the channel center where velocity will be at a maximum. This can then be converted into an average velocity, which for a parabolic flow profile will be $v_{\text{mean}} = 3v_{\text{max}}$, taking care to correct for the presence of any plug. Alternatively, velocity can be obtained from sequences of scaled digital photographs or thermal images (Sect. 2.2.4; Fig. 13c, d). The same scaled images can be used to estimate channel width. Width can also be obtained using a laser range finder, although

these are often very unreliable for low reflectance values, as is the case for basalt, as well as in heat haze or gassy conditions.

Channel depth is more difficult to estimate, but may be approximated from levee or flow front height, taking into account a basal layer of crust and the level of flow below bank (Fig. 13). Alternatively, a channel shape (square, rectangular, or semicircular) can be assumed, and the width used to approximate depth. Another option is to wait for the activity to stop, and directly measure the channel geometry directly with tape measure (Fig. 10), and then use this to estimate an average velocity using Eq. (10). Attempts have been made by plunging iron bars into the flow, but this is difficult to do due to access problems.

4.1.2 TADR from Volume, Heat Budget and Flow Area

Volume flux can also be estimated by subtracting sequential volumes of the flow field and dividing by the time between each volume estimate, which give a TADR. Volume estimates are either obtained from geometry of the flow estimated and DEM subtraction (see Sect. 3.1).

A common method to estimate TADR is the use of satellite sensor-derived data in the thermal infrared to apply the heat budget approach (See Harris 2013). This approach assumes a direct relation between heat flux and TADR where heat flux increases linearly with TADR, i.e.,

$$\text{TADR} = xA(Q_{\text{rad}} + Q_{\text{conv}}) \quad (18)$$

where A is the flow area and x is a scaling factor that depends on local conditions such as slope, degree of insulation and rheology. The basis of this relation is that the greater the TADR, the greater the potential for the lava to spread (under any given slope, insulation and rheological condition) and so attain a greater area. Hence, TADR scales with $A \times (Q_{\text{rad}} + Q_{\text{conv}})$. A simpler approach is to assume that flow area increases with TADR, so that

$$\text{TADR} = xA \quad (19)$$

In both cases (18 and 19) the solution becomes an empirical one which can be solved using historical data for TADR and A , or theoretically (See Harris 2013).

4.1.3 Conversion to Length

From a hazard assessment point-of-view, the most useful way to use effusion rate or TADR is to quickly assess how far a lava may extend at a given discharge rate. This follows on from Walker (1973) who showed that lava flow length (L) tends to scale with TADR, so that

$$\text{TADR} = x L \quad (20)$$

As with the relations of (18) and (19), this scaling needs to be carried as a function of flow composition, rheology, slope and insulation (Harris and Rowland 2009).

4.2 Rheological Properties

Defining rheological behavior of lava flows can be considered from two angles. The first is the lava mixture itself whose rheology depends on its chemical and petrographic characteristics. The second considers the flow as viewed as a whole, taking into account rheological controls on the flow dimension, velocity and morphology.

4.2.1 Rheology from Sample Characteristics

Defining lava rheology from sample characteristics must be performed on samples collected along the flow, either after emplacement or in situ. Lavas are made up of three phases. The melt phase, the solid phase (the crystals) and the gas phase (bubbles). Most lavas are defined as suspensions, meaning that their crystal cargo is less than the random maximum crystal packing. Although multiple models exist to constrain the viscosity of a magmatic suspension (see review by Kolzenburg et al. 2022), a simple protocol can be applied to define it. In this case, the viscosity of a lava is set as the apparent viscosity (η_{app}) of a mixture of polydisperse particles

(crystals and bubbles of various shapes and sizes) in a liquid phase (that is a silicate melt):

$$\eta_{app} = \eta_{melt} \cdot \eta_r = \eta_{melt}(T, X) \cdot \eta_{rc}(\phi c, r, \dot{\gamma}) \cdot \eta_{rb}(\phi b, Ca) \quad (21)$$

where the viscosity of the melt phase (η_{melt}) is Newtonian and depends on temperature (T) and composition (X). The relative viscosity due to the presence of a crystalline phase (η_{rc}) depends on the volumetric abundance of crystals (ϕc) and their aspect ratio (r), as well as strain rate ($\dot{\gamma}$). The relative viscosity due to the presence of bubbles (η_{rb}) depends on the volumetric abundance of bubbles (ϕb) and their capillarity number (Ca), which depends on the melt viscosity, bubble surface tension and strain rate.

The melt phase viscosity can be estimated from its composition and temperature using an appropriate model or directly by measuring the temperature-viscosity relationship (Russell et al. 2022; Schlke et al. 2024). This is straightforward to obtain for lava samples where the glass phase has been well preserved and the chemical composition (major elements) can be measured using a microprobe and temperature can be calculated from geothermometry (Putirka 2008). If the glass has not been preserved, but instead there is a microcrystalline groundmass, an alternative method is to calculate the bulk groundmass composition. This is achieved by subtracting the crystal chemical composition, using the average mass density of the crystals, from the bulk chemical composition of the sample (Ramírez-Urbe et al. 2021).

To estimate the effect of crystals and bubbles on the mixture viscosity, textural analysis is necessary. This is need to quantify the particle sizes, shapes (aspect ratio) and abundances (volume fraction). These characteristics are usually obtained from image analyses of thin sections and microphotographs (obtained from microscope or electronic microscope, back-scattered electron images) and using software such as ImageJ (see for example Shea et al. (2010), Robert et al. (2014), and Rhéty et al. (2017)). There are a large number of models to calculate the effect of crystals and bubbles

on lava viscosity considering either two phases (melt+crystals or bubbles) or three phases (melt+crystals+bubbles) (Harris and Allen III 2008). As of the time of writing, details of models found in the literature for magmatic suspensions are given in the review of Kolzenburg et al. (2022).

4.2.2 Rheology of a Lava Flow

The apparent rheological characteristics of a lava may be derived from flow dimension, velocity and morphology (e.g. Harris et al. 2011). During an eruption, lava viscosity can be estimated from using either the velocities of lava flowing within channels or at flow fronts (e.g. Harris et al. 2004, 2020; deGraffenried et al. 2021). Under the simplification that lava flows in a laminar fashion following a Newtonian or Bingham behavior, modification of the Jeffreys' (1925) equation and derivative equations (e.g., Eqs. 9–11) can be rearranged to estimate viscosity (Nichols 1939). This can be corrected for non-Newtonian behavior following Moore (1987) (see Harris and Rowland 2001). Apparent lava flow yield strength can also be obtained from its geometric parameters (Hulme 1974).

A third alternative is through direct in situ viscosity measurement (see Chevrel et al. (2019) for review). In over 70 years (1948 to 2024), only twelve studies on in situ lava rheology measurements have been published. However, there is currently ongoing development on new reliable field viscometers that could be deployed easily in the field to perform such measurement (Chevrel et al. 2023, Harris et al. 2024a). Recently, Harris et al. (2024b) deployed these new field instruments in Iceland (Litli-Hrútur 2023 eruption) and demonstrated that field viscometry can provide a rapid, accurate, and precise assessment of lava viscosity. Research is still needed, but further in situ field viscometry development holds potential for enabling routine measurements in the future.

5 Lava Flow Modelling-derived Hazard Assessment Products

Monitoring lava flows is often accompanied by forecasting most probable flow paths and areas of flooding. The simplest way of forecasting lava flow path is to define the line of steepest descent (Kauahikaua 2007). In Hawaii, the lines of steepest descent lines have been defined for use as a general guide in forecasting the initial lava flow path in future eruptions and to assist emergency managers (Kauahikaua et al. 2017). When coupled with models to assess potential cooling-limited run-out, flow models can also be used to evaluate areas and land type potentially threatened by inundation (Rowland et al. 2005; Harris et al. 2011).

Long-term hazard maps are a way of visualizing areas that will most likely be impacted (Chevrel et al. 2021; Favalli et al. 2012; Del Negro et al. 2013). However, when an eruption starts, a short-term hazard map is more appropriate because it focuses on the location of the ongoing eruption and represents a given scenario for that is restricted to the downhill area from the vent or the fissure and the zone at risk. Numerical models have been developed to include satellite-derived source terms (mostly TADR) and to allow real-time lava flow emplacement simulations and projections (Wright et al. 2008; Ganci et al. 2012; Harris & Rowland, 2015; Harris et al. 2019). Today, such maps are routinely produced during effusive eruptions at Hawaii (Neal et al. 2019), Mt Etna in Italy (Vicari et al. 2011) and Piton de la Fournaise, La Réunion (see below). Such maps are good communication tools between scientists and stakeholders. Nonetheless to ensure a common understanding and to help in building effective mitigation strategies they need to be designed based on the needs of the end users (Chevrel et al. 2022). For this, engagement with end users (local authorities) is necessary.

Lava flow forecasts usually involve provision of model-derived:

1. area that will potentially be covered
2. most likely path, and
3. distances the flow could reach.

Output depends on topography, slope, volume flux at the vent, total volume of lava emitted and/or the thermo-rheological properties of the lava. There are a number of numerical models that can be used to build short-term hazard maps but they all need to be pre-initialized, calibrated and validated (e.g., Harris and Rowland 2001; Vicari et al. 2011; Hyman et al. 2022). Pre-initialization and calibration rely on collection of source term data, and validation involves retrospective analyses on previous eruptions to best fit the model to reality.

5.1 Example of Piton de la Fournaise (La Réunion)

Since 2014 at Piton de la Fournaise (Le Réunion), lava flow inundation areas have been forecast and modeled through a satellite-data driven protocol (Chevrel et al. 2022; Harris et al. 2017; 2019). This protocol determines the probable inundation area and flow runout distances via the DOWNFLOWGO numerical code that is a combination of DOWNFLOW (Favalli et al. 2005) and FLOWGO (Harris and Rowland 2001). While DOWNFLOW provides the path of steepest descent and probable lava flow inundation area, FLOWGO calculates the maximum cooling-limited runout of lava for a given effusion rate. To operate this protocol on a routine basis during each eruption, a retrospective analysis of the April 2018 eruption was carried out (Harris et al. 2019). As part of the protocol, an initial hazard map is shared within the first hours of any eruption and, when needed, the map is updated as eruption conditions evolve (new vents opening, extension of tubes, change in TADR) (Fig. 16). The maps provide a fundamental communication tool between scientists and the authorities and have been developed

through iterative dialog with local civil protection. Figure 16 shows the delivered products during the operational forecasting and monitoring response at Piton de la Fournaise for the December 2020 eruption. This includes a map of the eruption site where the line of steepest descent and the probable lava flow paths are shown together with the location of the eruptive vent and of the flow front. This short-term hazard map can be better constrained and updated during the eruption as TADR becomes better constrained, and evolves (Fig. 16b, c), and cross-checks on lava flow outline are obtained either from satellite imagery airborne photogrammetry (Fig. 16d), and/or field observations.

6 Lava Flow Monitoring: The Future?

Technology and scientific capabilities are constantly improving and evolving, as new techniques come on line, existing instrumentation becomes improved, and prices become lower. One could argue that for monitoring, in some areas, we do not need any further reduction in image spatial resolution. For example, for lava flow modelling a DEM spatial resolution of 10 m is more than adequate (Chevrel et al. 2018b). However, what we do need is the best possible temporal resolution, so as to track lava flow spreading, topographic changes and update lava flow models with the most up-to-date DEMs. Given the time scales involved in emplacement of a rapidly extending lava flow a few tens of minutes would be ideal, whereas for longer lasting events (years) a few days-to-weeks may be sufficient. The key is, to balance data loads with scenario needs and processing capabilities. In populated areas the need for regular and fast processing of data and delivery of product, as developed by Copernicus Emergency Management Service (e.g., Fig. 4), is more pressing than in remote and unpopulated areas.

Of course, lava is hot so one of the best means of tracking it is remotely and in the infrared. However, no terrestrial sensor is currently perfect for tracking active lava. Fundamentally,

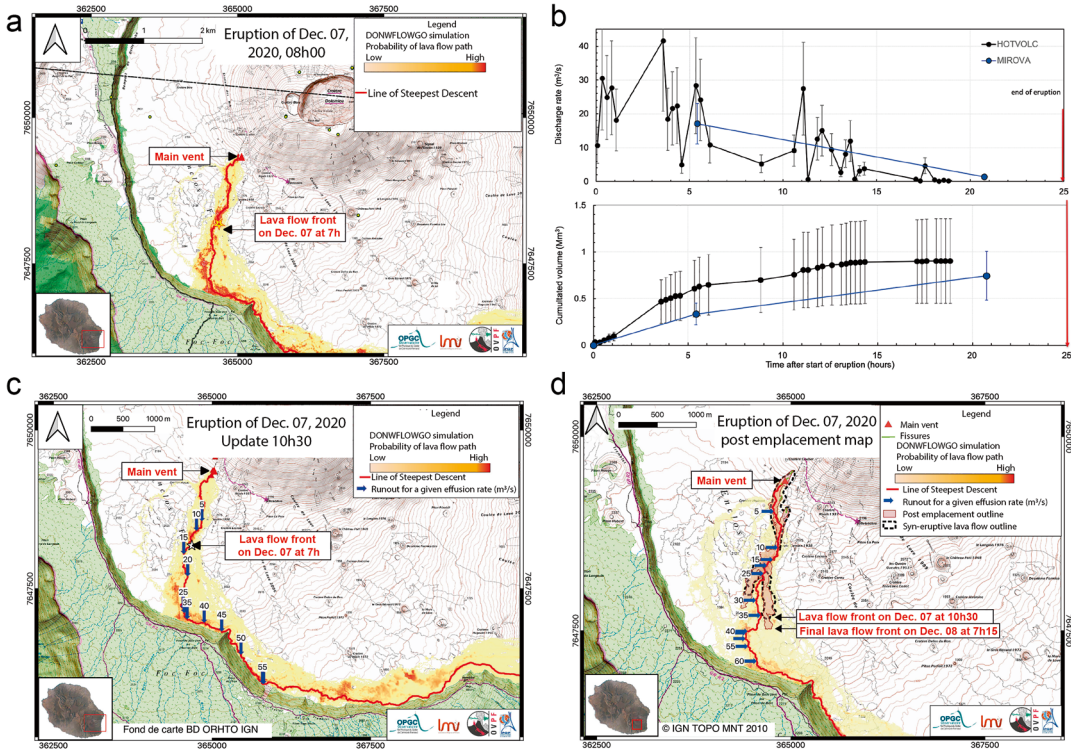


Fig. 16 Operational forecasting and monitoring response at Piton de la Fournaise (La Réunion) for the December 2020 eruption. **a** First map produced on December 7, 2020 at 8h00 local time. **b** TADR and cumulative volume since the start of the eruption obtained by the HOTVOLC (Gouhier et al. 2016) and MIROVA (Coppola et al. 2016) systems. **c** Updated map produced on December 7, 2020 at 10h30 local time.

d Final map showing the probability of lava flow invasion, runout distances as function of TADR and the final lava flow field outline obtained by airborne photogrammetry (post emplacement outline). The lava flow outline drawn from the Sentinel-2 image acquired on December 7 at 10h30 is also shown (syn-eruptive outline). This map was produced after the end of the eruption. Taken from Chevrel et al. (2022)

gain settings are usually too low so that saturation occurs at 60–120 °C, meaning all pixels over an active lava flow are saturated. A pressing need is for at-least one waveband in the mid and/or thermal infrared with a saturation of at-least 800 °C.

UAS, that has literally taken off over the last decade, represent a promising tool to monitor lava flows; but onboard thermal imaging payloads need to be developed for lava flow temperatures. To track entire lava flow fields, advances in UAS portable thermal imaging technology needs to be associated with improving capabilities for UAS to cover larger areas and for building orthomosaics from potentially thousands of images covering tens of km².

Seismicity and infrasound have been shown, especially during the 2018 eruption of Kilauea, capable of tracking the evolution of an effusive event, especially in terms of vent location and effusive intensity (Patrick et al. 2019). Further advances would be to track flow advance, where ground-based radar and/or InSAR could be used. This would be ideal for cloudy regions, but frequencies of current InSAR acquisitions could be increased to a few hours or so.

While fast and simple non-physical 1D and 2D models are systematically used to forecast lava flow paths and velocities, and to prepare short term hazard maps (e.g., Harris et al. 2019; Chevrel et al. 2022; Ganci et al. 2012; Herault et al. 2009; Neal et al. 2019), more

sophisticated physics-based models are still not well-enough developed to produce a timely forecast (Dietterich et al. 2017). Development of faster numerical models accompanied by automatization of satellite data integration are needed so that such capabilities can be used as operational tools for efficient near real time lava flow propagation forecasting (e.g., Hyman et al. 2022; Cappello et al. 2022).

Automated reporting systems and observatory data bases are advancing all the time, so as to ease the administrative and reporting load of volcano observatory staff. Crowd sourcing through social media will, without a doubt, continue to develop as a resource to contribute to following effusive eruption impacts as well as distributing warning, alerts and information (Wadsworth et al. 2022). Conversely, there are other basics that are slow to improve: funding is never enough, staff numbers are always too low, helicopter time is frequently non-existent, and working hours are long, as are kilometers walked. The field practitioner will thus always argue in terms of reducing equipment weight and bulk along with a well-defined duty and task lists.

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Thermal Monitoring of Volcanoes from Space

Diego Coppola

Abstract

Volcanic eruptions transfer a significant amount of heat from the earth's crust to the atmosphere. Thermal monitoring of volcanoes from space aims to detect and measure this heat in real-time (or near real-time) and track its variations in space and time before, during, and after an eruption. In this chapter, I introduce the physical principles of thermal remote sensing applied to volcanology as well as the main systems and the online tools currently used for operational thermal monitoring of volcanoes. These systems are based on platforms and sensors with different spatial, temporal, and spectral characteristics, each of which is well situated to detect volcanic phenomena with specific spatial and temporal scales (from the slow appearance of small fumaroles to the very rapid emission of large lava flows). In particular, I present the range of metrics currently used to quantify a thermal anomaly from space and I highlight

how the integration of multiple datasets provides a deeper insight into the volcanic activity in progress. Finally, by using real cases I provide a series of best practices in analysing and interpreting thermal signals during unrest phases or eruptive crises. This chapter summarizes the great progress made by this discipline in the last 20 years and highlights the fundamental contribution that thermal remote sensing can make in monitoring various types of volcanic activity.

1 Introduction

The transport of heat is undoubtedly the engine of terrestrial dynamism in many of its forms, especially in producing magmatism and volcanism (Sigurdsson 2015). Heat can be transported through the earth's interior by several processes, and on active volcanoes, it is commonly associated with the storage and ascent of magma and volatiles (Jaupart and Mareschal 2011). Most volcanic energy is dissipated as heat (Pyle 2015) and its quantification before, during, and after an eruption is crucial for understanding and monitoring volcanoes. This heat manifests on the earth's surface through the appearance of volcanic thermal features (VTF_s), i.e. the spatial elements with temperature(s) above the “background”, having variable sizes and whose nature is associated with some volcanic processes

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(Oppenheimer et al. 1993). The definition of VTF just described introduces one of the key concepts of thermal remote sensing of volcanic activity, namely the background. In this work the background is defined as the surface temperature (or radiance) of the environment surrounding a VTF.

Different types of VTF_S can be identified from space (Fig. 1), roughly linked to active (eruptive) or quiescent (non-eruptive) conditions. Based on their maximum temperature, the VTFs are generally subdivided into three main groups:

- high-temperature VTFs ($> 100\text{ }^{\circ}\text{C}$): include (a) active lava flows (Wright and Flynn 2003), (b) active lava lakes with ‘rift-ing’ centers (Spampinato et al. 2008), (c) active lava domes with a cooling carapace (Sahetapy-Engel and Harris 2008), (d) open vents containing magma whose level varies with time (Harris and Stevenson 1997) and (e) high-temperature fumaroles (Oppenheimer et al. 1993);
- low-temperatures VTFs ($< 100\text{ }^{\circ}\text{C}$): include (f) intra-crater lakes (Oppenheimer 1993) and (g) low-temperature fumaroles and hot springs (Vaughan et al. 2012). Additional low-T VTFS are represented by rapidly cooled pyroclastic flows (Carter and Ramsey 2009) and lava flow margins (Pinkerton et al. 2002);
- very low-temperature VTFs ($\sim$ ambient temperature): diffuse heat emissions at the spatial scale of a crater (Mannini et al. 2019) or entire volcanic edifice (Girona et al. 2021; Chan et al. 2021), with anomalies of up to a few $^{\circ}\text{C}$ above the background.

These categories are only a simplification of a range of continuous volcanic processes, in which the transition from one to the other (i.e. from non-eruptive to eruptive and vice versa) is often gradual.

Commonly, thermal monitoring of volcanoes from space is focused on identifying high- and low-temperature VTFs (often referred to simply

as thermal anomalies), and following their changes in near real-time (NRT; Harris 2013; Coppola et al. 2020). However, recent studies have also shown that an increase in diffuse heat can be also measured from space (Mannini et al. 2019), even on the scale of the entire volcanic edifice ($> 10\text{ km}^2$) several years before some eruptions (Girona et al. 2021). Although these pioneering studies pave the way for new developments in this discipline, in this work I will focus on the application of remote sensing techniques to track the appearance and evolution of the first two groups of VTFs.

Since the early 1980s, satellites with infrared (IR) capabilities have been used to detect, locate and characterize VTFs, with ever-increasing precision. A series of works have traced the history of this discipline in recent decades (the reader is invited to read Harris 2013; Ramsey and Harris 2013; Ramsey et al. 2021, for an exhaustive review), pointing out two main operational objectives of space-based thermal monitoring of volcanoes: (1) assess the occurrence of precursor signals that may indicate an imminent eruption and (2) follow the evolution of eruptive crises and provide additional elements for the continuous assessment of the associated hazard.

These ambitious objectives are increasingly possible due to three main strengths that characterize the space-based disciplines facing natural hazards:

- the *synoptic view*, which allows having an overall picture of the events in progress;
- the *global applicability*, which allows observing any volcano on earth, in the same way, regardless of the difficulty of access;
- *safety, continuity, and longevity* which allow collecting data safely, continuously, and for long periods, even during emergencies (when more conventional monitoring systems may have gaps).

Nevertheless, at present, there is still no satellite mission expressly dedicated to monitoring volcanoes from space, and the current systems are based on spacecraft and sensors with spatial,

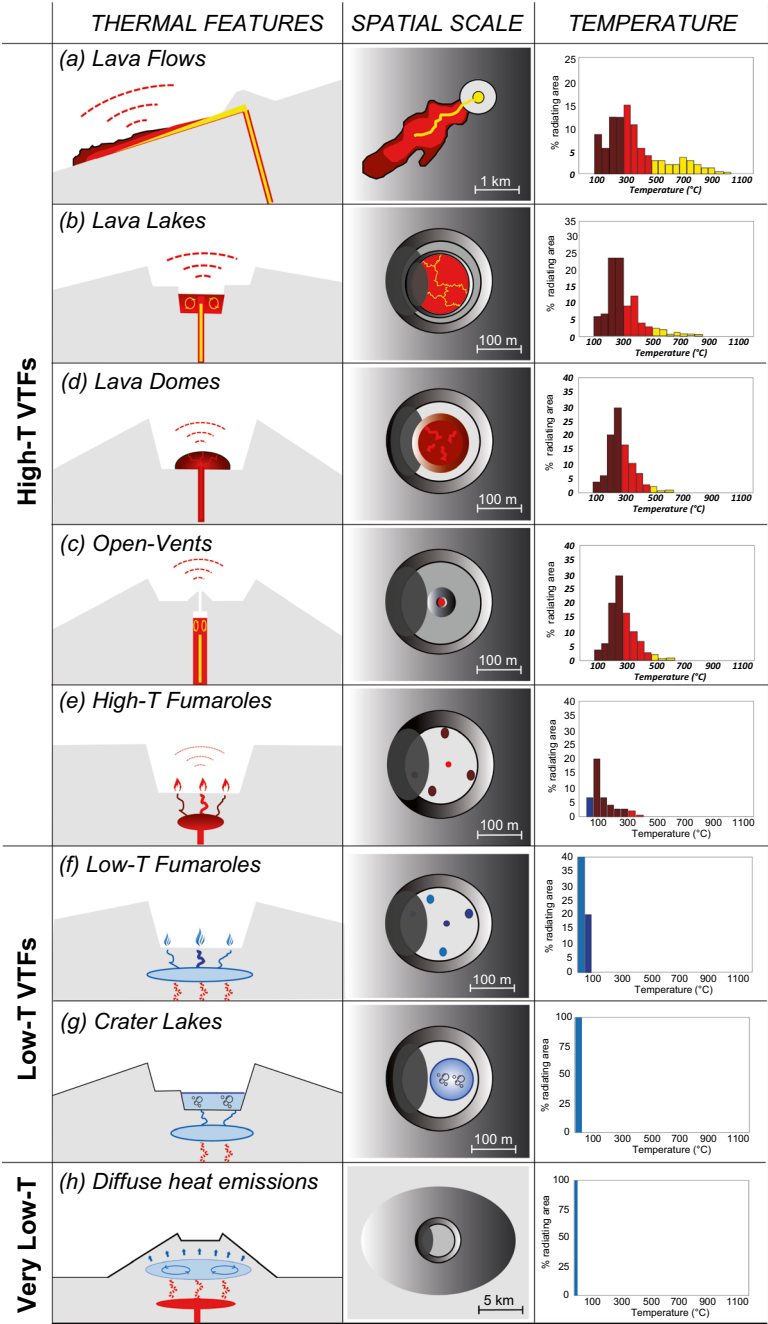


Fig. 1 Compilation of the main Volcanic Thermal Features (VTFs) tracked using thermal remote sensing and subdivided into: 1) High-T (>100 °C) VTFs: **a** active lava flows, **b** convective lava lakes, **c** active lava domes, **d** open-vent volcanoes, **e** high-temperature fumaroles; 2) Low-T (< 100 °C) VTFs: **f** low-temperature fumaroles, **g** crater lakes; 3) Very Low-T (~ambient) VTFs: **h** diffuse heat emissions; (modified from Oppenheimer et al. 1993). The right column illustrates the typical Temperature Distribution for the

associated VTF (modified from Oppenheimer et al. 1993 and Wright et al. 2011). The central column illustrates the representative spatial extension of the associated VTF. The left column represents a simplified vertical sketch of the volcanic structures/processes at the origin of each VTF. The VTF's colors refer to the following temperature ranges: blue (T<100 °C), brown (100–300 °C), red (300–500 °C), yellow (T>500 °C)

temporal, and spectral resolutions inherited from non-volcanological observables that limit the full potential of the discipline in near-real-time (Ramsey et al. 2021).

A recent review on the usage of space-based thermal data by volcanological observatories (Coppola et al. 2020) has highlighted that most of these do not have their own monitoring tools but rely on external systems and international collaborations (Lowenstern et al. 2022; Pritchard et al. 2022). Very often these external systems are based on the analysis of data processed by different groups, with different algorithms and/or coming from sensors having different spectral, spatial and temporal resolutions. As there is still no international coordination among thermal remote sensing working groups (Bally 2012; CEOS 2013, 2015; Pritchard et al. 2022), this variability can pose ambiguity in the interpretation of the data that can be problematic to communicate to decision-makers (Pallister et al. 2019; Lowenstern et al. 2022; Pritchard et al. 2022).

In this chapter, I will describe the different tools that have been developed during the last decades for the thermal monitoring of volcanoes from space. The purpose is to provide an overview of the state of the art of the various systems currently operating and to provide a theoretical basis for processing and interpreting thermal data from different satellite platforms.

The work is therefore divided into three parts. In Part I the basic concepts of thermal remote sensing will be provided and the characteristics of the sensors and algorithms most used in volcanic monitoring will be briefly described. In Part II, some case studies will be presented to highlight the advantages and limitations of the sensors and techniques described above, according to the type of activity in progress. Some best practices will also be provided to be used during eruptive crises for a correct analysis and interpretation of satellite thermal data. Finally, Part III will present some methods to obtain second-level products that provide direct information on some fundamental volcanological parameters. In particular, applications will be presented to

obtain effusion rate during lava-flow-forming eruptions, the level of an active lava lake, or the temperature of an intracrater lake. The results show the broad potential of thermal remote sensing in decoding a multitude of types of volcanic activity.

2 Part I: Basic Principles and Techniques

2.1 Fundamentals Laws

The fundamental law governing electromagnetic radiation is the Planck's law according to which the blackbody spectral radiance $B(\lambda, T)$ leaving a surface at absolute temperature T (K) is equal to:

$$B(\lambda, T) = \frac{2hc^2}{\lambda^5 (\exp(hc/k\lambda T) - 1)} \quad (1)$$

where λ is the wavelength (m), k is the Boltzmann constant ($\sim 1.38 \times 10^{-23} \text{ m}^2 \text{ kg s}^{-2} \text{ K}^{-1}$), h is the Planck constant ($\sim 6.63 \times 10^{-34} \text{ m}^2 \text{ kg s}^{-1}$), and c is the speed of light in the medium ($\sim 3.00 \times 10^9 \text{ m s}^{-1}$).

The total power emitted per unit area at the surface (radiant flux density M_{rad} in W m^{-2}), may be found by integrating the Planck's law over all wavelengths, and over the solid angles corresponding to the hemisphere above the surface:

$$M_{rad} = \sigma T^4 \quad (2)$$

where σ is the Stefan–Boltzmann constant ($\sim 5.67 \times 10^{-8} \text{ W m}^{-2} \text{ K}^{-4}$).

These two equations determine the main characteristics of thermal radiation (Fig. 2) according to which:

- the Planck curves never cross;
- the wavelength at which the maximum emission occurs decreases with increasing temperature (*Wien's law*; Fig. 2a), and
- the spectral radiance at each wavelength as well as the radiant flux density increases with the temperature (Fig. 2b).

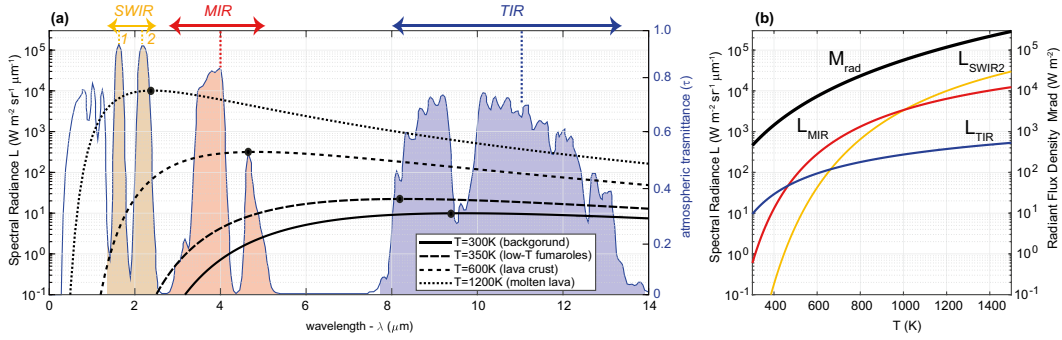


Fig. 2 **a** Planck curves (black thick lines) associated to temperatures commonly found in volcanic environments (from Harris 2013): molten lava (~1200 K), crusted lavas (~600 K), low-temperature fumaroles (~350 K), and background (~300 K). The black dots indicate for each curve the wavelength of maximum radiation (Wien's law). The shaded coloured fields indicate the location of the main atmospheric windows in the SWIR (orange), MIR (red) and TIR (blue) whose transmittance

(τ) is shown on the right axis. The dashed vertical lines indicate the central wavelengths of channels commonly used by IR sensors (SWIR₁: ~1.6 μm, SWIR₂: ~2.2 μm, MIR: ~4 μm), and TIR: ~11 μm; see also Table 1). **b** Temperature-dependent increase of spectral radiance $L(\lambda)$ (Eq. 1) and radiant flux density M_{rad} (Eq. 2) in the SWIR (orange), MIR (red), and TIR (blue) channels. For the colours refer to the online version of the figure

Equations 1 and 2 are valid for a black body, an idealized physical body that absorbs all incident electromagnetic radiation. However, when dealing with real surfaces, the blackbody radiation must be corrected for the spectral emissivity $\varepsilon(\lambda)$, so that the radiance emitted by the real surface (L_{SE}) becomes:

$$L_{SE}(\lambda, T) = \varepsilon(\lambda) \bullet B(\lambda, T_s) \quad (3)$$

where T_s is the surface temperature (in K). The emissivity $\varepsilon(\lambda)$ is a wavelength-dependent property that describes the effective ability of the surface to absorb (and emit) thermal energy. For real bodies, the emissivity is always less than 1 (grey body emissivity) and in the case of lava surfaces, it generally varies between 0.6 and 1 (Rogic et al. 2019; Ramsey et al. 2019; Thompson and Ramsey 2021). The emissivity of lava is also influenced by temperature, with a general tendency to decrease for increasing temperatures (Rogic et al. 2019; Ramsey et al. 2019; Thompson and Ramsey 2021).

The radiance measured by a sensor at the top of the atmosphere (L_{TOA}) is also affected by additional factors (Fig. 3) the most important of which are solar reflection, atmospheric scattering and attenuation and sky radiation (or

atmospheric emission). A simplified model can therefore describe L_{TOA} as:

$$L_{TOA}(\lambda) = \tau(\lambda) \bullet \{\varepsilon(\lambda) \bullet B(\lambda, T_s) + \rho(\lambda) \bullet L_d(\lambda)\} + L_u(\lambda) \quad (4)$$

where T_s is the surface temperature (assumed homogeneous), $\rho(\lambda)$ is the reflectivity of the surface (commonly assumed $\rho(\lambda) = 1 - \varepsilon(\lambda)$), $\tau(\lambda)$ is the atmospheric transmittance, and $L_d(\lambda)$ and $L_u(\lambda)$ are the downwelling and upwelling spectral radiances, respectively.

The downwelling radiance $L_d(\lambda)$, is basically the sum of three components (Fig. 3): the direct solar radiation, the radiation scattered by the atmosphere onto the target and the downward sky radiation. These three components are reflected back towards the sensor (as a function of $\rho(\lambda)$), and attenuated by the atmosphere by a factor equal to $\tau(\lambda)$. The upwelling radiance $L_u(\lambda)$, is instead composed of the radiation scattered and emitted by the atmosphere towards the sensor.

Three main atmospheric windows allow the observation of the earth in the infrared with a minimum of atmospheric attenuation (Fig. 2a). These windows constitute the regions of the electromagnetic (EM) spectrum

Table 1 List of satellite/sensors and associated features, currently used for operational thermal monitoring of volcanic activity. Three main classes of sensor are distinguished based on the spatial and temporal resolutions (after Harris 2013)

Class	Satellite	Sensor	Start	Temporal resolution	Spatial resolution ^(*)	Central wavelength (l)				Saturation radiance (L_{max})/temperature (T_{max})			
						SWIR1	SWIR2	MIR	TIR	SWIR1	SWIR2	MIR	TIR
TM-Class	Terra	<i>ASTER</i>	Dec 1999	Variable	30 m (SWIR) 90 m (TIR)	1,65 (band 4)	2,16 (band 5)	×	11,3	55	15,8	×	370 K
	Landsat 8/9	<i>OLI/TIRS-2</i>	Feb 2013/ Sep 2021	~8 days	30 m (SWIR)	1,61	2,20	×	×	32	11	×	×
	Landsat 8/9	<i>TIRS/TIRS-2</i>	Feb 2013/ Sep 2021	~8 days	100 m (TIR)	×	×	×	10,8	×	×	×	360 K
	Sentinel 2A/2B	<i>MSI</i>	Jun 2015/ Mar 2017	~5 days	20 m (SWIR)	1,61	2,19	×	×	70	24,5	×	×
AVHRR-Class	GCOM-C	<i>SGLI</i>	Dec 2017	~3 days	250 m	1,63	×	×	10,8	50	×	×	340 K
	NOAA-18/ NOAA-19	<i>AVHRR</i>	May 2005/ Feb 2009	~0.5 days	1100 m	1,61	×	3,74	10,8	70	×	335 K	335 K
	Terra/ Aqua	<i>MODIS</i>	Dec 1999 /May 2002	~0.5 days	1000 m	1,63	2,13	3,96**	11,02	70	22	500 K**	390 K
	Sentinel 3	<i>SLSTR</i>	Feb 2016	~0.5 days	1000 m	1,61	2,22	3,74**	10,85	45,0	69,8	500 K**	400 K
GOES-Class	Suomi NPP/ JPSS-1	<i>VIIRS</i>	Oct 2011/ Nov 2017	~0.5 days	750 m 375 m	1,61	2,25	4,05**	10,76	71,2	31,8	634 K**	340 K
	MSG-1	<i>SEVIRI</i>	Aug 2002	15 min	3000 m	1,64	×	3,74	11,45	72,5	×	353 K	343 K
	Hima- wari 8	<i>AHI-8</i>	Oct 2014	10 min	2000 m	1,61	2,26	3,90	10,8	75	×	335 K	335 K
	GOES-16	<i>ABI</i>	Nov 2016	5 min	1000/2000 m	1,61	2,25	3,85	11,02	77,1	23,9	400 K	335 K

* Nominal Resolution at Nadir

**Fire Channel (Low-Gain MIR channel)

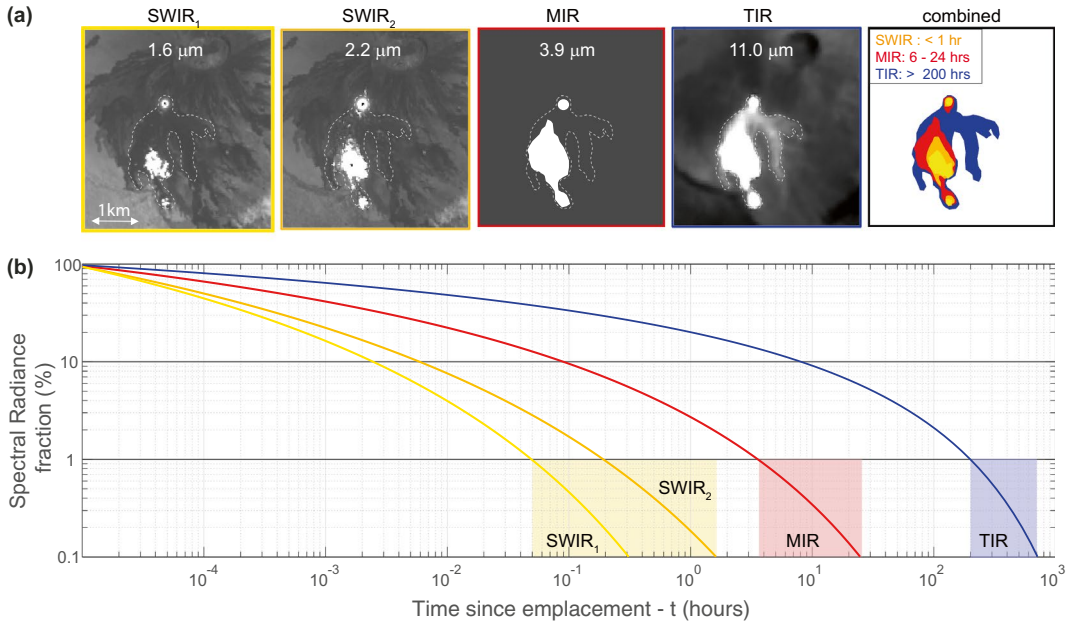


Fig. 4 **a** Multispectral view of a lava flow emplacing at Piton de la Fournaise volcano (Landsat 8 image acquired on 11 Oct, 2015). The hot lava flow appears as bright pixels seen at different wavelengths. An increase in the “hot area” is visible passing from SWIR₁ (1.6 μm–30 m/pixel) to SWIR₂ (2.2 μm–30 m/pixel) to TIR (11 μm–100 m/pixel) channels (see Table 1 for Landsat 8 characteristics; please note that the MIR (3.9 μm) image (artificial) is shown for demonstration purposes only,

as the Landsat 8 has no bands at this wavelength.). **b** Theoretical decrease of SWIR, MIR, TIR radiance with time. The curves are calculated using Eq. 2 and 7, by setting the coefficients $a=146$ and $b=0.0164$, typical for pahoehoe flows (Hon et al. 1994). Based on this cooling model, the SWIR radiance is roughly reduced to less than 1% in less than 1 h, the MIR in 6–24 h, and the TIR in more than 200 h

thermal remote sensing systems try to detect the presence of a VTF and quantify its intensity.

Equation 1 can be inverted to obtain the pixel-integrated temperature T_{pix} :

$$T_{pix}(\lambda) = \frac{hc}{k\lambda \ln\left(1 + \frac{2hc^2}{\lambda^5 L_{pix}}\right)} \quad (7)$$

Also called brightness temperature. The pixel-integrated temperature is the theoretical temperature that a homogeneous ground element (the whole pixel) should have to produce the measured radiance at the given wavelength. Although this temperature has no volcanological meaning, as we will see later it is sometimes used to quantify the intensity of a thermal anomaly due to its dependency on the fractional areas (f_i) and temperatures (T_i) of the VTF. In fact, an increase in the area or in the temperature of a

VTF generates an increase in $L_{pix}(\lambda)$ and $T_{pix}(\lambda)$ as indicated by the Eqs. 6 and 7.

2.3 Temperature Distribution of Volcanic Thermal Features

VTFs are not characterized by a homogeneous temperature, but rather are composed of a number (n) of thermal components which define variable distribution of temperatures (Fig. 1). Generally, these components are not randomly scattered but are spatially organized with maximum temperature(s) centered on the magma/gas emission point(s), and temperatures gradually lower as you move away from it. This overall pattern characterizes most of the VTFs (Oppenheimer et al. 1993; Wright and Flynn 2003; Wright et al. 2011; Sahetapy-Engel and

Harris 2008; Coppola et al. 2009), and generally produces unimodal or bimodal temperature distributions with a pronounced positive skewness (right panels in Fig. 1). This means that, for temperatures higher than the modal value, the area occupied by each component tends to decrease. The characteristics of the temperature distribution are strongly related to heat transfer properties and cooling rates acting on the VTF (see next paragraph) but are also dependent on the chemistry, and eruption style and can be temporarily altered by a surge in magma/gas emission (Wright et al. 2011).

Given the link between temperature and wavelength, this pattern commonly produces an increase in the area of the VTF when viewed in the SWIR, MIR, and TIR, respectively (Fig. 4a).

2.4 Cooling Rate and “Thermal Age”

Although satellite images provide an instantaneous view of the ground, the characteristic cooling behaviour of a VTF can be used to assess the “thermal age” (t) of the radiating surface (Harris et al. 2007a, b):

$$t = a \bullet e^{-bT_s} \quad (8)$$

where T_s is the surface temperature, and a and b are the exponential parameters governing the cooling rate (Hon et al. 1994). This approach, called thermal image chronometry by Harris et al. 2007a, b, was initially applied to pahoehoe lava flows but can be eventually adapted to other VTFs, by taking into account their appropriate cooling models (Harris et al. 2007a, b). Solving Eq. 8 for T_s and substituting into Eq. 1 we note that the radiance decreases very rapidly in SWIR, and much more slowly in MIR and TIR (Fig. 4b). For example, by using the exponential coefficient for pahoehoe lavas (Hon et al. 1994), I calculated the time necessary for the cooling of the lava surface to decrease the initial radiance of two orders of magnitude (Fig. 4b). This simple model indicates that the SWIR radiance reduced to 0.1–1% within 1 h, the MIR radiance within 6–24 h, and the TIR

radiance within 200–600 h (Fig. 4b). In terms of volcano monitoring, this cooling rates suggest that the SWIR bands can detect lava surface emplaced (or heated) since a couple of hours at most, while TIR bands can sense lava surfaces emplaced several days/weeks before the image acquisition.

Given the link between surface age, temperature, area, and wavelength the following conclusions can be drawn:

- The extent of a thermal anomaly (area of the VTF) increases from SWIR to TIR;
- The minimum detectable temperature decreases from SWIR to TIR;
- The age of the «sensed» surface increases from SWIR to TIR.

2.5 Sensors and Resolutions

The previous paragraphs have highlighted that both L_{pix} and T_{pix} , are affected by both VTF- and sensor dependent parameters (Eq. 6 and 7). In particular the VTF-dependent parameters include the area (A_i) and temperature (T_i) of each thermal component characterizing the volcanic thermal feature (VTF) while sensor-dependent parameters include the wavelength (λ) and pixel size (A_{pix}) characterizing each sensor. It is therefore clear that sensor characteristics play a key role in the identification and quantification of thermal anomalies.

Over the past 50 years, several satellites and sensors with IR-capabilities have been used for volcano observations. Ramsey et al. 2021 count 36 successive sensors in their review, with at least 12 currently operational and routinely used for volcano monitoring on a global or local scale (Table 1).

Based on their resolutions, Harris 2013 distinguishes three main classes of orbital IR sensors (Fig. 5), named after the first sensor in each family: GOES (Geostationary Operational Environmental Satellite: 4-km pixels, 15-min cadence), AVHRR (Advanced Very-High-Resolution Radiometer: 1-km pixel; 6-h cadence), and TM (Thematic Mapper: 60-m

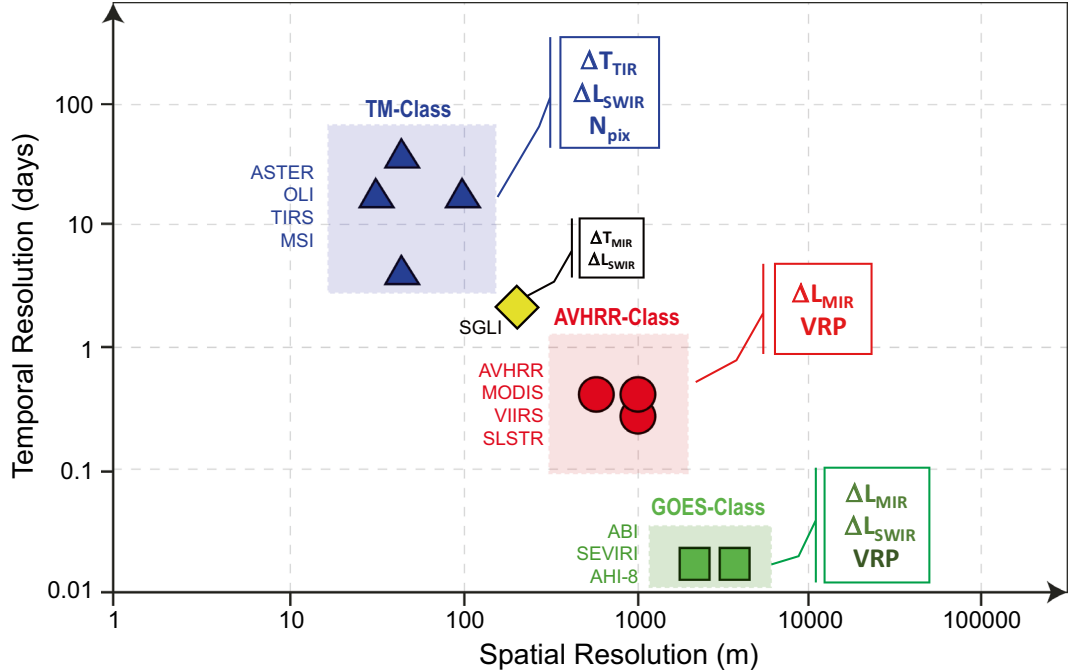


Fig. 5 Temporal and spatial resolution of common IR sensors used for thermal monitoring of volcanoes and subdivided in three classes (modified from Harris 2013). Multiple instruments of the same class may have

the same spatial and temporal resolution. Boxes list the metrics typically provided by each sensor’s class (see the text for explanation of each metric)

pixel; 16-day cadence). However, the continuous technological evolution is gradually bridging the gap between these classes. An example is the new GCOM-C (Global Change Observation Mission—Climate), launched in 2017 by the JAXA space agency, which mounts the second-generation global imager (SGLI) sensor. This system has intermediate characteristics between the TM-Class and AVHRR-Class sensors (Fig. 5) allowing acquisition of SWIR and TIR images, every 3 days with a resolution of 250 m.

In addition, the different sensors are distinguished by the number of available bands, by the region of the electromagnetic (EM) spectrum where they are located, and by the saturation values that determine their dynamic range (Table 1). As described in the previous paragraph, all these characteristics influence the capability or effectiveness of detecting and quantifying a thermal anomaly of volcanic origin. In particular, the spatial and spectral resolution determine what are the

minimum area and the temperature that the VTF must have to be detected. Conversely, temporal resolution affects the ability of a given system to detect sudden changes in activity. The combination of these characteristics is therefore critical in determining the application that can be made of the IR data for volcanic monitoring. Table 1 lists all these characteristics for the 12 sensors commonly used in the thermal monitoring of active volcanoes (Fig. 5).

2.6 Hotspot Detection Algorithms

The purpose of any satellite thermal volcanic monitoring system is to promptly detect the presence of a VTFs on the ground and to monitor its changes in space or time. This activity is based on the definition of three key concepts: the “background”, the “threshold” and the “anomaly”.

Several types of algorithms have been developed to detect hotspot-contaminated pixels (pixels containing a VTF or part of it) by using different sensors and wavelengths (for a review see Steffke and Harris 2011 and Harris 2013). All these algorithms are based on the calculation of a specific threshold (expressed in terms of radiance, temperature, or wavelength-specific thermal indices) which separate the background from the anomalous pixels. According to Steffke and Harris 2011, all the algorithms can be grouped into four categories based on the method used to calculate the threshold:

- *Spectral (fixed threshold) algorithms*: these algorithms are based on the calculation of spectral indices generally expressed in the form of a Normalized Difference Index (NDI) equation:

$$NDI = \frac{Band(x) - Band(y)}{Band(x) + Band(y)} \quad (9)$$

where x and y are two IR bands. The presence of a VTF strongly increases this kind of index because of the different responses of the two bands to the presence of sub-pixels hot components. A sub-pixel hotspot is therefore detected when the index value of a pixel exceeds certain fixed thresholds (Table 2). Wright et al. (2002) first introduced this type of automatic approach, by using the Normalized Thermal Index (NTI) to analyze MODIS (Moderate Resolution Imaging Spectroradiometer) data. Recently, similar indices, called Normalized HotSpot Indices (NHIs) have been applied to SWIR channels of TM-Class sensors (Table 2) by using one or multiple fixed thresholds to determine if the pixel is hot or not (Genzano et al. 2020). A new spectral index, called the thermal eruption index (TEI) and based on the short-wave infrared (SWIR) and thermal infrared (TIR) bands of Landsat 8 was recently introduced by Afuaristama et al. (2018).

- *Spatial (contextual) algorithms*: these algorithms determine the threshold based on the comparison of each pixel with its

surroundings. When a pixel exceeds the radiance of the adjacent pixels by a certain value (threshold) this is considered hot. Generally, these algorithms are applied on temperature data (not on radiance data) by setting a pixel temperature difference (ΔT) of at least 5 °C as a threshold. The Volcanic Anomaly Software (VAST; Higgings and Harris 1997) is the first algorithm of this kind where the region of interest is compared, image after image, with an adjacent region, not volcanic, but with similar topographical characteristics.

- *Temporal algorithms*: in these cases, the radiance of a pixel is considered “anomalous” if it exceeds its normal variability over time. The ALICE (Absolutely Local Index of Change of the Environment) index is used to identify thermal anomalies:

$$\otimes_V(x, y, t) = \frac{V(x, y, t) - \mu_V(x, y)}{\sigma_V(x, y)} \quad (10)$$

where $V(x, y, t)$ is the signal (e.g., spectral radiance or brightness temperature) at the time t for each pixel (x, y) of the scene, while $\mu_V(x, y)$ and $\sigma_V(x, y)$ are the temporal mean and standard deviation, calculated over multiyear time series of cloud-free satellite records, acquired under the same observational conditions (same month and hours of the day). In this case, the threshold represents the typical value of the pixel considering its natural variability as obtained from the previous temporal analysis. The Robust Satellite Techniques (RST; Tramutoli 1998) originally used to identify thermal anomalies, through GOES-class data, is the archetypal of this kind of temporal algorithm. This approach has also been successfully applied to data from AVHRR- and TM- class sensors (Pergola et al. 2004; Genzano et al. 2021).

- *Hybrid algorithms*: these are the most complex and combine several aspects of spectral, spatial, and temporal approaches at the same time. For example, the Okmok algorithm (Dean et al. 1998) incorporates both spatial and temporal aspects typical of VAST and RST algorithms, while the MIROVA (Coppola et al. 2016) uses some spectral

Table 2 Normalized different indices commonly used to detect volcanic hotspots by using the *spectral (fixed threshold) algorithms* (see text for details)

Index	Bands		Equation index	Threshold		Satellite(Sensor)	Reference
				Nighttime	Daytime		
Normalized thermal index	NTI	MIR(3.959 mm) TIR(12.02 mm)	$NTI = \frac{L_{3.9} - L_{12}}{L_{3.9} - L_{12}}$	-0.8	-0.6	Terra(MODIS) Aqua(MODIS)	Wright et al. 2002
Normalized hotspot index	NHI _{SWIR}	SWIR ₁ (1.6 mm) SWIR ₂ (2.2 mm)	$NHI_{SWIR} = \frac{L_{2.2} - L_{1.6}}{L_{2.2} - L_{1.6}}$	N.D.	0	Landsat (OLI) Sentinel2 (MSI) Terra(ASTER)	Genzano et al. 2021
	NHI _{SWNIR}	NIR (0.8 mm) SWIR1 (1.6 mm)	$NHI_{SWNIR} = \frac{L_{1.6} - L_{0.8}}{L_{1.6} - L_{0.8}}$	N.D.	0		
Thermal eruption index	TEI	SWIR1 (1.6 mm) TIR(11.0 mm)	$TEI* = \frac{L_{1.6} - \frac{(L_{11})^2}{10L_{1.6}^{max}}}{L_{1.6} + \frac{(L_{11})^2}{10L_{1.6}^{max}}} \cdot \frac{(L_{11})^2}{(L_{1.6}^{max})^2}$	N.D.	0.1	Landsat (OLI & TIRS)	Aufaristama et al. 2018

* $L_{1.6max}$: maximum spectral radiances detected at 1.6 μ m for each scene

indices in combination with a contextual analysis of the same in the surrounding of the volcano.

The recent advances made in computational power and artificial intelligence (AI) are now permitting new classes of algorithms which instead of being based on the above principles are based on the capability of AI to iteratively learn complex models. Examples directly applied to volcanic hot spot detection include machine learning techniques such as artificial neural network (Piscini and Lombardo 2014) or random forest regressions (Corradino et al. 2022).

where L_{hotpix} and T_{hotpix} are the pixel-integrated radiance and temperature of the hot-spot-contaminated pixels (the pixel containing a VTF), and L_{bk} and T_{bk} are the pixel-integrated radiance and temperature of the background (generally calculated from pixel(s) surrounding the anomaly).

Very often, because the VTF is very large or because blurring of the satellite images (due to the sensor's point spread function), several adjacent pixels can be detected by an algorithm. In these cases, the total excess radiance $\Delta L_{tot}(\lambda)$, sourced by the whole VTF, is calculated as the sum of the excess radiance of all the hotspot-contaminated pixels:

2.7 Metrics Commonly Used for Thermal Remote Sensing of Volcanoes

Once a pixel contaminated by a hotspot has been detected (hereby referred to with the subscript *hotpix*), it is useful to measure its “excess of radiance” (ΔL_{hotpix}), or “excess of temperature” (ΔT_{hotpix}), with respect to the background:

$$\Delta L_{hotpix}(\lambda) = L_{hotpix}(\lambda) - L_{bk}(\lambda) \quad (11)$$

$$\Delta T_{hotpix}(\lambda) = T_{hotpix}(\lambda) - T_{bk}(\lambda) \quad (12)$$

$$\Delta L_{tot}(\lambda) = \sum_{k=1}^{N_{pix}} \Delta L_k(\lambda) \quad (13)$$

where N_{pix} is the number of pixels above the background, and ΔL_k is the excess radiance of the k^{th} pixel.

Two other simple metrics are used to monitor changes in a VTF within multiple images. These are the number of alerted pixels (N_{pix}) in each scene and the maximum temperature difference (ΔT_{max}), which only takes into account the pixel with the highest ΔT_{hotpix} . The total excess of radiance (ΔL_{tot}), the number of alerted pixels (N_{pix}) and the maximum temperature difference (ΔT_{max})

are three of the simplest metrics that allow describing and monitoring a VTF (Table 3).

Unfortunately, these metrics are still affected by sensor-dependent factors, such as the pixels' size, wavelength, and saturation. This makes comparing or merging different datasets a complicated operation especially in a quantitative way.

To derive robust metrics that are exclusively related to the VTF, such as the area of the VTF (A_{hot}), its effective radiating temperature (T_{hot}), and the radiative power ϕ_{rad} (the heat radiated by the VTF), a basic assumption is commonly used. This assumption is based on a simplification that sees the VTF described by a single effective temperature (T_{hot}) such as to produce a radiant power equivalent to that effectively emitted from all the thermal components characterizing the VTF (Pieri and Baloga 1986). In this simple scenario, the pixel integrated radiance is equal to:

$$L_{hotpix}(\lambda, T_{hotpix}) = f_{hot} \bullet B(\lambda, T_{hot}) + (1 - f_{hot}) \bullet B(\lambda, T_{bk}) \quad (14)$$

where f_{hot} is the fractional area of the VTF ($f_{hot} = A_{hot}/A_{pix}$) and $B(\lambda, T_{hot})$ and $B(\lambda, T_{bk})$ are the blackbody spectral radiance of an idealized surfaces at T_{hot} and T_{bk} , respectively.

If T_{bk} is retrieved from the pixels adjacent to the hot one, Eq. 14 can be solved by assuming one of the two other unknowns (T_{hot} or A_{hot}). This method, commonly known as two-component model (Marsh et al 1980; Dozier 1981) is often applied by assuming a range of realistic values for T_{hot} and calculating an upper and lower boundaries for the areas within which the true value of A_{hot} is found (Harris 2013):

$$A_{hot} = \frac{L_{hotpix}(\lambda) - B(\lambda, T_{bk})}{B(\lambda, T_{hot}) - B(\lambda, T_{bk})} \bullet A_{pix} \quad (15)$$

Accordingly, the radiant power of the VTF (ϕ_{rad}) can be calculated as:

$$\phi_{rad} = A_{hot} \sigma \varepsilon (T_{hot}^4 - T_{bk}^4) \quad (16)$$

More complex systems can be solved by using two or more bands (see Harris 2013 for a review) allowing simultaneous calculations of the areas and temperature of more thermal

components. However, the solution of these systems is often conditioned by the wavelengths used, the presence of unsaturated channels, and by the assumptions of some unknown (i.e. temperature of some component).

An alternative approach to calculate the radiative power of a VTFs, is the Volcanic Radiative Power (VRP after Coppola et al. 2013), a method inherited from the more common Fire Radiative Power (FRP) proposed by Wooster et al. (2003). This method uses only a single MIR band and is founded on the quasi-linear relationship existing between L_{MIR} and M_{rad} for temperatures between 600 and 1500 K (cf. Figure 2b). In fact, for this range of temperatures, the MIR radiance can be approximate by $L_{MIR} \approx \alpha T^4$, a relationship very similar to Eq. 2. Accordingly, the VRP (in Watt) can be calculated as:

$$VRP = \Delta L_{MIR} \bullet \frac{\sigma \varepsilon}{\alpha \varepsilon_{MIR}} \bullet A_{pix} \quad (17)$$

where ΔL_{MIR} is the excess of radiance, σ is the Stefan-Boltzmann constant, ε is the emissivity of the VTF over all wavelengths, ε_{MIR} is the emissivity over the MIR spectral band, and α is the wavelength-dependent constant expressing the proportionality described above. One of the advantages of this method is that Eq. 17 can be applied to any sensor with a MIR channel, independently from the spatial resolution, by adapting A_{pix} and α to the sensor specifications (Aveni et al. 2023). For example, the application of Eq. 17 to the MODIS data ($\lambda_{MIR} = 3.959 \mu\text{m}$) expects to consider, $A_{pix} = 1 \times 10^6 \text{ m}^2$, and $\alpha = 2.96 \times 10^{-19}$ while in the case of VIIRS (Visible Infrared Imaging Radiometer Suite), 750 m resolution bands at $\lambda_{MIR} = 4.050 \mu\text{m}$, the parameters become, $A_{pix} = 0.75 \times 10^6 \text{ m}^2$ and $\alpha = 2.88 \times 10^{-19}$ (Wooster et al. 2003, Li et al. 2018; Campus et al. 2022).

Unlike the metrics described above (ΔT , ΔL , or N_{pix}) which are conditioned by the characteristics of the sensor, the VRP is almost exclusively dependent on the characteristics of the VTF and therefore allows the integration of multiple datasets into a single homogeneous

time series (Campus et al. 2022; Aveni et al. 2023). On the other hand, the method works with an error $\pm 30\%$ exclusively if the integrated temperature of the VTF is comprised between 600–1500 K, where the approximation holds (Wooster et al. 2003). Given the typical distribution of the VTF (Fig. 1) this limit implies that the VRP is inadequate for estimating the radiant power of low-temperature VTFs, while is particularly indicated to measure the radiant power emitted by the younger portion of the VTF having $T_{hot} \geq 600$ K and emplaced for no more than 12–24 h (Coppola et al. 2009; Fig. 2b).

Campus et al. (2022) has shown how VRP and FRP measured on different volcanic targets through the analysis of MODIS and VIIRS data are robustly correlated with each other, and provide congruent estimates regardless of the sensor used. The simplicity with which the VRP/FRP is calculated and its multi-sensor robustness makes this parameter extremely suitable for NRT measurements, especially through a variety of sensors, characterized by the presence of low-gain MIR channels (i.e. the fire channel; Table 1).

3 Part II: Operational/ Applications: How to Interpret the Satellite Thermal Data for Volcano Monitoring

3.1 Near Real Time (NRT) Volcanic Hotspot Detection Systems

In Table 3 we have collected the main features of 19 independent online tools that currently provide near-real-time images/information used for satellite thermal monitoring of volcanoes (locally or globally).

Most of the systems have been developed by international research groups, while only a few have been developed expressly by institutes responsible for volcanic monitoring. In the list, we have also included the Fire Information for

Resource Management System (FIRMS), as well as two web platforms (AWS EO-Browser and Google Earth Engine) that allow the NRT visualization and processing of some satellite data in the cloud. Although these systems have not been specifically developed to monitor volcanoes, they are routinely used by some observatories in case of ongoing eruptions (Coppola et al. 2020).

Some of these systems have internal web pages that are not accessible to the public, others have only limited access, while still others allow open access to their NRT products. These products are here grouped into three categories which provide more in-depth information on the volcanic phenomenon underway:

- *Infrared Images (SWIR, MIR, or TIR)*: allow to verify the presence or not of a VTF, and eventually locate and measure its spatial dimension. The images also allow evaluation of satellite viewing conditions and the presence of volcanic clouds/plumes that can mask or attenuate the thermal signal.
- *Intensity*: allow quantification of the thermal anomaly using a specific metric that depends on the type of sensor and the algorithms used (see Table 3).
- *Time-series*: allow the evaluation of the time trend of thermal emissions. The comparison between the data measured in NRT and the data measured in the previous hours, days, or months allows a more objective evaluation of the phenomena in progress.

As evident from Table 3, each of these systems uses specific sensors and/or algorithms that make it particularly useful for one application but not for another. Depending on the type of volcanic phenomenon in progress some sensors are more efficient than others for thermal monitoring. In the next chapter, I present three case studies (Sabancaya, Etna, and Bezymianny) to show the advantages and disadvantages of different sensors in tracking volcanic phenomena having very different spatial, temporal, and energy scales (i.e. slow unrest of an andesitic

Table 3 List of hotspot detection systems and online tools useful for IR volcano monitoring

Developer	System	Coverage	Sensor	Bands	Spatial resolution	Temporal resolution	Images	Time series	Metric	Reference	Website
INGV	HOTSAT	Specific targets (Europe, Africa)	MODIS	MIR, TIR	1 km	6–12 h				Ganci et al. 2011	<i>Internal web page</i>
			SEVIRI	MIR, TIR	~5 km	15–30 min					
INGV	AVHotRR	Specific target	AVHRR	MIR, TIR	1 km	6–12 h				Lombardo 2016	<i>Internal web page</i>
			SEVIRI	MIR, TIR	~5 km	15–30 min					
IMAA	RSTvolc	Specific target	AVHRR	MIR, TIR	1.1 km	6–12 h				Pergola et al. 2015	<i>Internal web page</i>
			MODIS	MIR, TIR	1 km	6–12 h					
AVO	Unnamed	Specific targets Alaska; Aleutianes; Kamchatka	AVHRR	MIR, TIR	1.1 km	6–12 h				Dean et al. 2002	<i>Internal web page</i>
			MODIS	MIR, TIR	1 km	6–12 h					
			VIIRS	MIR, TIR	375–750 m	6–12 h					
LMV	HOTVOLC	Specific targets (Europe, Africa)	SEVIRI	MIR, TIR	~5 km	15–30 min	✓	✓	ΔL_{MIR}	Gouhier et al. 2016	http://hot-volc.opgc.fr/www/index.php
	GEO-URP	North, Central, South America; Pacific ocean	GOES, HIMA-WAR	MIR, TIR	~5 km	15–30 min	✓	✓	ΔT_{MIR}^{Total} Heat Flux	Thompson et al. (2022)	http://ivis.eps.pitt.edu/GOES/
HIGP	HOTSPOT	North, Central, South America; Pacific ocean	GOES	MIR, TIR	~5 km	15–30 min	✓	✓	–	Patrick et al. 2016	http://goes.higp.hawaii.edu/
HIGP	MODVOLC	Global	MODIS	MIR	1 km	6–12 h		✓	ΔL_{MIR}^{VRP}	Wright et al. 2004	http://modis.higp.hawaii.edu/
USGS	VOLCVIEW	Specific targets (Alaska; Aleutianes; Kamchatka; Pacific ocean)	AVHRR	MIR, TIR	1.1 km	6–12 h	✓			Shneider et al. 2014	https://volcview.wr.usgs.gov/vv-gui/
			MODIS	MIR, TIR	1 km	6–12 h	✓				
			VIIRS	MIR, TIR	375–750 m	6–12 h	✓				

(continued)

Table 3 (continued)

Developer	System	Coverage	Sensor	Bands	Spatial resolution	Temporal resolution	Images	Time series	Metric	Reference	Website
University of Turin	MIROVA	Specific targets (Global scale)	MODIS	MIR	1 km	6–12 h	✓	✓	VRP	Coppola et al. 2016	http://www.mirovaweb.it/
			VIIRS	MIR	750 m	6–12 h	✓	✓	VRP	Campus et al. 2022	
			Sentinel2 MSI	SWIR	20 m	5 days	✓	✓	Npix	Massimetti et al. 2020	
			Landsat 8 OLI	SWIR	30 m	16 days	✓	✓	Npix		
KVERT	VOLSAT-VIEW	Specific targets (Kamchatka&-Kuriles)	AVHRR	MIR, TIR	1.1 km	1–2 h	✓			Gordeev et al. 2016	http://volcanoes.smislab.ru/static/index.sh
			MODIS	MIR, TIR	1 km	6–12 h	✓				
			VIIRS	MIR, TIR	375–750 m	6–12 h	✓				
University of Tokyo	REALVOLC	Specific targets (Asia;Oceania; North & South America)	MODIS	MIR, TIR	1 km	6–12 h	✓	✓	ΔT_{MIR}	Kaneko et al. 2010	http://vrs-serv.eri.u-tokyo.ac.jp/realvolc/
			SGLI	SWIR, TIR	250 m	3 days	✓	✓	ΔT_{TIR} DL_{SWIR}	Kaneko et al. 2020	
			HIMAWARI	MIR, TIR	~5 km	15–30 min	✓	✓	ΔT_{MIR}	Kaneko et al. 2010	
NOAA	NIGHTFIRE	Global	VIIRS	SWIR, MIR	375–750 m	6–12 h		✓	$N_{pix, MIR}$ FRP	Elvidge et al. 2013	https://eog-data.mines.edu/products/nf
NASA	FIRMS	Global	MODIS	MIR	1 km	6–12 h		✓	$N_{pix, MIR}$ FRP	Davies et al. 2009	https://firms.modaps.eosdis.nasa.gov/
			VIIRS	MIR	375–750 m	6–12 h		✓	$N_{pix, MIR}$ FRP		
JPL	AVA	Specific targets (Global)	ASTER	TIR	90 m	variable	✓		ΔT_{TIR}	Linick et al. 2014	https://ava.jpl.nasa.gov/

(continued)

Table 3 (continued)

Developer	System	Coverage	Sensor	Bands	Spatial resolution	Temporal resolution	Images	Time series	Metric	Reference	Website
GSJ	ASTER image database	Specific targets (Global)	ASTER	TIR	90 m	variable	✓		–	Urai (2011)	https://gbank.gsj.jp/vsldb/image/index-E.html
Cornell University	AVTOV	Specific targets (Lat America)	ASTER	TIR	90 m	variable		✓	$N_{pix,TIR}$, ΔT_{TIR}	Reath et al. 2019a	https://www.wovo-dat.org/
GFZ	MOUNTS	Specific targets (Global)	Sentinel2 MSI	SWIR	20 m	5 days	✓	✓	N_{SWIR}	Valade et al. 2019	http://mounts-project.com/home
Universidad Católica del Norte	VOLCA-NOMS	Specific targets (Latin America)	Sentinel2 MSI	SWIR	20 m	5 days	✓	✓	ΔL_{SWIR}	Layana et al. 2020	http://volcanoms.ckcler.org/
IMAA	NHI tool	Global	Sentinel2 MSI	SWIR	20 m	5 days	✓	✓	N_{SWIR} , ΔL_{SWIR}	Genzano et al. 2020	https://nicogen-zano.users.eearthengine.app/view/nhi-tool
			Landsat 8 OLI	SWIR	30 m	16 days	✓	✓	N_{SWIR} , ΔL_{SWIR}		
Google	Google earth engine	Global	Multiple collections polar satellites	SWIR, MIR, TIR	20 m to 1 km	6 h to 16 days	Cloud API for satellite Imagery				https://earthengine.google.com/
AWS	Sentinel hub	Global	Multiple collections polar satellites	SWIR, MIR, TIR	21 m to 1 km	7 h to 16 days	Cloud API for satellite Imagery				https://www.sentinel-hub.com/

volcano, sudden paroxysm at a basaltic volcano and occurrence of a pyroclastic flow at a silicic lava dome).

3.2 Case Studies

3.2.1 Slow Unrest at Sabancaya Volcano (Peru)

The Sabancaya volcano (Peru) began to erupt in November 2016 and is still ongoing at the time of this writing (Coppola et al. 2022). The eruption was preceded by a long unrest phase characterized by the appearance and widening of hot fumaroles on the bottom of the crater, accompanied by increasing degassing, seismicity, and inflation below the volcanic edifice (Jay et al. 2015; Reath et al. 2019a, 2019b; Coppola et al. 2022). This precursory thermal activity was detected by different IR sensors (Fig. 6) at very different times depending on the spatial, temporal, and spectral resolution of each system.

The Advanced Spaceborne Thermal Emission and Reflection (ASTER), through its resolution of 90 m in the TIR (Table 1), first detected thermal anomalies (pixels above background) in 2003 and was able to track a subtle but gradual increase in ΔT in the following years (Reath et al. 2019a; Fig. 6a). Starting from 2012, thermal anomalies were also detected in the MIR band of the VIIRS using the 375 m resolution data product (Coppola et al. 2022; Fig. 6b), and only two years later they were also detected by MODIS MIR band at 1 km resolution (Fig. 6c). Starting from 2014, the SWIR channels of Landsat 8—OLI (Operational Land Imager) and Sentinel 2—MSI (Multispectral Instrument), with a resolution of 30 and 20 m, respectively, begin to detect thermal anomalies on the bottom of the crater, which erupted on 6 November 2016 (Fig. 6d). The eruption was characterized by the slow extrusion of a lava dome, accompanied by fluctuating thermal anomalies (0.5–25 MW), by irregular degassing and by

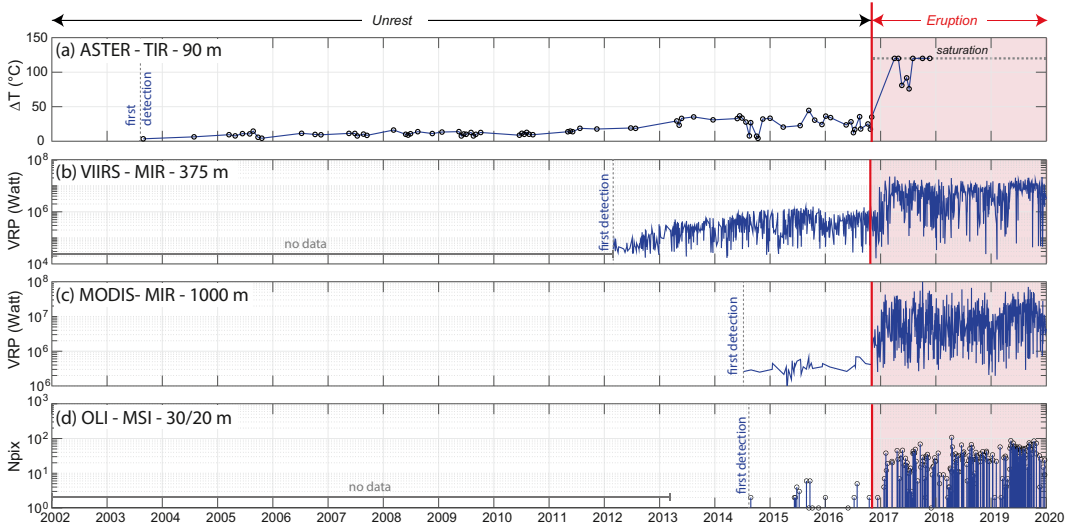


Fig. 6 Thermal unrest was detected at Sabancaya volcano (Peru) by: **a** ASTER-TIR data at 90 m resolution (data from Reath et al. 2019a); **b** VIIRS-MIR data at 375 m resolution (from Coppola et al. 2022); **c** MODIS-MIR data at 1 km resolution (from Coppola et al. 2022); **d** Landsat 8 (OLI) and Sentinel 2 (MSI) SWIR data at 20 m resolution (from Coppola et al. 2022). The

red vertical line indicates the beginning of the eruptive phase, marked by the area shaded in red. The grey dashed line indicates the timing of the first thermal anomaly detected by each sensor. Note that between 2000 and 2014 the MODIS was operational but there were no thermal anomalies detected at Sabancaya

variable explosive activity (Coppola et al. 2022) producing repeated vulcanian ash plumes (500–5000 m) above the crater (cf. Figure 8a). This intense activity often saturated the ASTER-TIR sensor data and precluded it from following the evolution of the eruption using the ΔT metric (Fig. 6a). On the contrary, MODIS-derived and VIIRS-derived VRP were continuously recorded throughout the eruption (Fig. 6b, c). together with the number of hot pixels (Npix) detected by SWIR sensors (Fig. 6d).

Sabancaya's case is exceptional in the duration of the thermal unrest and highlights how the combination of multiple IR sensors, having different spatial resolution, temporal resolution and wavelengths allows observatories to follow the activity both in unrest and in eruptive phases.

Nonetheless this example outlines how the detection of precursory thermal signals, remains strongly dependent on the availability of frequent, high resolution thermal data.

3.2.2 Sudden Paroxysms at Mt. Etna (Italy)

Etna is well known all over the world for its persistent open-vent activity, characterized by continuous gas emissions, mild-explosive activity from the summit craters, and recurrent effusive activity from central, lateral, or eccentric vents (Branca and DelCarlo 2005). However, in recent years it has become increasingly evident that the activity described above may be frequently punctuated by mid-to-violent explosive events, occurring at the summit craters, also called paroxysmal episodes (Andronico et al. 2021). These episodes are characterized by a rapid progression (minutes to hours), that see the summit activity transitioning from discrete strombolian explosions to continuous lava fountains several hundred meters high often accompanied by the emplacement of fast lava flows and/or by the emission of ash plumes that can reach more than 10 km in height (Calvari et al. 2021). The rapid evolution of these events requires almost continuous monitoring, which from a space-born remote sensing perspective can only be guaranteed by geostationary satellites (Ganci et al. 2012a). However, the low resolution of

the latter does not allow investigators to obtain spatial details (i.e. which crater is responsible for fountaining, on which flank the lava flow is emplacing, what is the length of the lava flow, etc.) which is instead possible through the use of TM-Class sensors (Table 3). In Fig. 7 we show the example of the 1st paroxysmal episode of 2021 (16 February 2021) in which various sensors/algorithms are combined to provide a detailed picture of the phenomena that occurred in just 48 h.

The VRP obtained from SEVIRI through the RST_VOLC algorithm (Marchese et al. 2021) is coupled to the VRP measured by MODIS and VIIRS through the MIROVA algorithm (Coppola et al. 2016), and integrated by high-resolution SWIR observations, provided by Sentinel 2 before the paroxysm (Massimetti et al. 2020) and by ASTER-TIR data, recorded the day after the event, thanks to the ASTER Urgent Request Protocol (Ramsey and Flynn 2020).

The Sentinel 2 image acquired on 16 February, at 10:00 (UTC), shows the thermal state of the summit craters ~6 h before the paroxysm (Fig. 7b). At this time the central (Bocca Nuova and Cratere Voragine) and the south-east (South-East Crater and New Crater of Southeast) crater sectors are punctuated by intense high-temperature thermal anomalies. Of these, the New Southeast Crater (NSEC) appears to be the most active, likely because of the source of increasing strombolian activity. The northeast crater is instead covered by a thick blanket of water vapor. In these pre-paroxysm conditions, MODIS (1 km) and the VIIRS (750 m) measured a VRP of about 100–200 MW (Fig. 7a), a range of values compatible with the inferred strombolian activity at the summit craters (Coppola et al. 2020). On the contrary, SEVIRI does not show particular thermal anomalies likely because of its low spatial resolution (3 km resolution in the MIR; Table 1). A few hours later, at 16:00 a VRP of 280 MW was detected by SEVIRI (Fig. 7a). Thanks to the sampling rate of 15 min, SEVIRI was able to detect a sudden increase of VRP at 16:15 UTC (760 MW), associated with the start of a paroxysmal episode sourced by the NSEC (Andronico

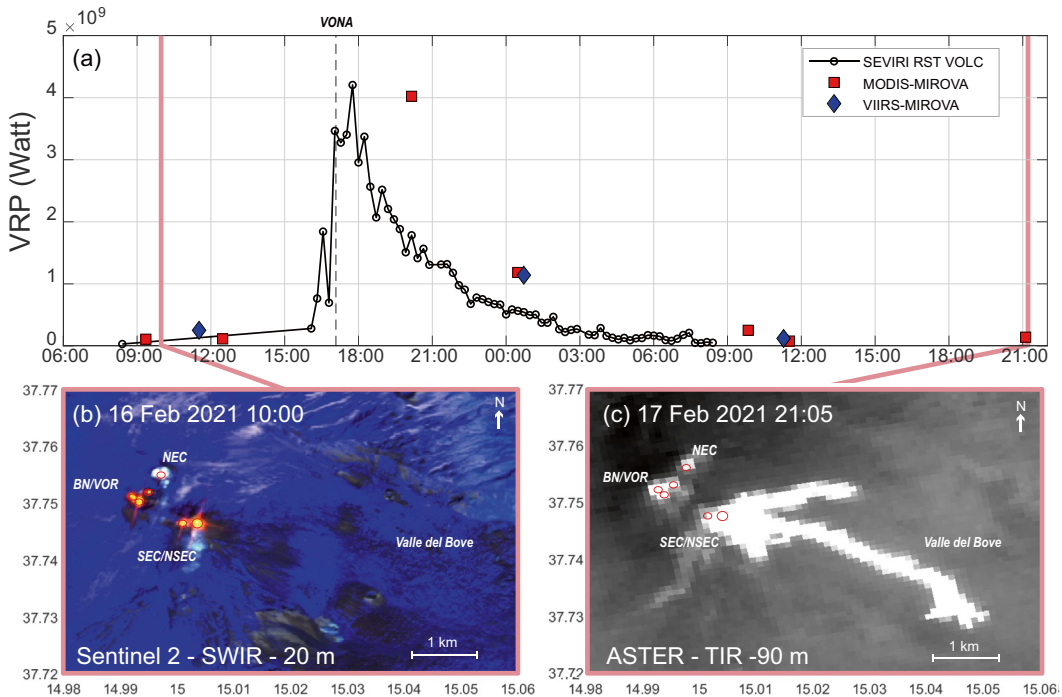


Fig. 7 **a** Time-series of VRP recorded during the 16 February 2021 paroxysm of Etna volcano (Italy) by SEVIRI (black line with dots), MODIS (red squares), and VIIRS (blue diamond). **b** Sentinel 2 image acquired on 16 February 2021 at 10:00 UTC (Band combination

12-11-8a). **c** ASTER image acquired on 17 February 2021 at 21:05 UTC (Band 14) showing the extension of the lava flow which was fed by the paroxysmal activity at SEC/NSEC sector

et al. 2021). At 17:00 the VRP reached more than 3000 MW and was followed, at 17:05 by a Volcano Observatory Notice for Aviation (VONA) issued by INGV, indicating an ash cloud height of 10 km and ash fallout in Catania town (VONA/INGV 2021). The thermal activity peaked at 17:45 UTC after which a gradual decrease was recorded in the following 24 h. Both MODIS and VIIRS have lost the onset and peak phase although in the following hours both measured VRP values consistent with the general waning trend recorded by SEVIRI (Fig. 7a). The ASTER image, acquired on 17 February at 21:05, shows that the paroxysmal episode was accompanied by the emplacement of a lava flow within the upper sector of the Valle del Bove (Fig. 7c). The flow had covered $\sim 2.05 \text{ km}^2$ probably in a few hours, and reached a maximum length of $\sim 5 \text{ km}$.

This example shows how each sensor was able to provide specific information regarding the current eruption, but not others. In fact, using a multi-sensor approach it was possible to obtain a more complete view of the sudden Etna's paroxysm by tracing its thermal evolution both in in space and time.

3.2.3 Pyroclastic Flow(S) at Bezmyanny Volcano (Russia)

Satellite thermal data have often been used to detect and map pyroclastic density currents (PDC) (Carter and Ramsey 2010; Krippner et al. 2018; Flynn and Ramsey 2020). Due to the rapid cooling of their surface deposits PDC are often mapped using TIR channels capable of detecting low-temperature VTFs associated to these deposits also several days after their emplacement (Carter and Ramsey 2009;

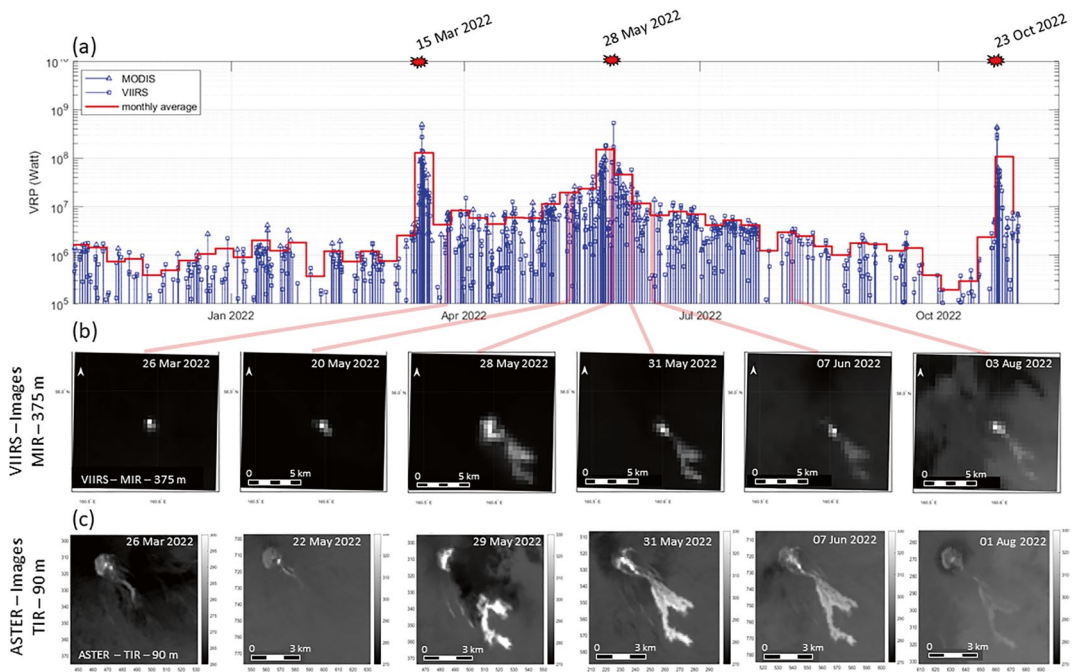


Fig. 8 **a** Time series of the VRP recorded on the Bezymianny volcano in 2022. Three peaks of thermal activity are recognized, corresponding to phases of extrusive-explosive cycles of the lava dome which took place on 15 March, 28 May and 23 October 2022. It should be noted that, unlike the other two events, the explosion of 28 May was preceded by a monthly-long period of increase in VRP. The explosion generated a PDC more

than 6 km long, which was detected by both the VIIRS **b** and the ASTER **c**. While the VIIRS images acquired in the MIR at 375 m mainly show the high temperature thermal activity at the level of the crater, the ASTER images acquired in the TIR at 90 m are able to accurately detect the thermal structure of the PDC and its gradual cooling throughout the following months

Reath et al. 2014; Ramsey 2016; Ramsey and Flynn 2020). In Fig. 8 I show a recent example associated with the eruptive activity of Bezymianny (Russia) which took place in 2022. According to the Kamchatka Volcanic Eruptions Response Team (KVERT), three major explosions occurred during this period (on 15 March, 28 May and 23 October 2022; VONA/KVERT Information Release 2022a, b, c). Notably, after the explosion of 15 March 2022, strong fumarolic activity and incandescent lava dome were continuously reported by KVERT and produced a thermal signal in the MIR and TIR detectable by both the VIIRS (Fig. 8b) and the ASTER sensors (Fig. 8c). The VRP time series derived from MODIS and VIIRS MIR data (Fig. 8a), indicates that this summit activity was accompanied by an increasing heat flux that clearly accelerated after

20 May 2022. At Bezymianny volcano, similar increases have been observed numerous times in the past, and often constitute a precursor signal indicative of an impending explosion (Girina 2012; van Manen et al. 2010; Reath et al. 2016). On 28 May, 2022 at 07:26 UTC a major explosion was reported by VAAC-KVERT (VONA/KVERT Information Release 2022a, b, c), and produced an ash plumes drifting ESE and rising 10–15 km above sea level. The explosive activity produced a major PDC on the E flank, which was tracked by both VIIRS and ASTER sensors (Fig. 8b and c). The deposit extends for more than 6 km in the SE direction and consists of at least two main branches. This is clearly visible in the ASTER image acquired the day after the explosion through the ASTER URP (Ramsey and Flynn 2020), which shows, in great detail,

the extension of the deposit (Fig. 8c). In the following ASTER images, acquired on 31 May, 7 June and 1 August, it is possible to observe the gradual cooling of PDC as well as its thermal structure, possibly associated to variable surface/deposit properties such as thickness, roughness, vesicularity (Carter et al. 2009). On the other hand, MIR images acquired after the explosion by VIIRS indicate that the high-temperature VTFs in the summit area were strongly reduced, in accordance with a gradual decrease in VRP (Fig. 8a). The gradual decrease in the heat VRP stops again at the beginning of October when a new, sudden phase of growth heralds the explosion of 23 October 2022 (Fig. 8a).

4 Best Practices During Unrests and Eruptive Crises

During an unrest phase or an eruptive crisis, a series of best practices are needed to correctly interpret space-based thermal anomalies in (near)-real-time. These are closely related to the knowledge of the limits and uncertainties associated with thermal measurements.

4.1 Image Supervision or Classification

In addition to the time-series analysis, it is often important to supervise every single image to correctly evaluate the quality of the data, the nature of the thermal anomaly, and the real trend of the thermal flux. Supervision has the purpose of evaluating the quality of the images and filtering the time series to exclude (or reduce) the effects of (i) clouds or volcanic plumes, (ii) instrument viewing geometry, (iii) fires or anthropogenic heat sources, and (iv) false alerts.

4.1.1 Clouds and Volcanic Plumes

The presence of clouds or volcanic plumes can partially, or totally, mask a thermal anomaly. These factors strongly affect the interpretation of a single datapoint since, for example,

a sudden reduction in the thermal flux can be interpreted as an effective decrease in activity while, in reality, it is due to the presence of clouds or ash plume(s) within the pixel. It is therefore useful to evaluate the impact of clouds and plumes on the monitored thermal parameter (e.g. ΔT , ΔL , N_{pix} , or VRP timeseries). From a quantitative point of view, this evaluation is somehow complex (because it requires precise characterization of the atmospheric conditions just above the heat source) preferring instead a qualitative evaluation. Some automated systems provide cloud indexes (i.e. fraction of cloudy pixels within the whole scene) that can be coupled to heat flux time series for data quality control. This approach is especially useful in the post-analysis of long time series, but can be misleading in the case of real time monitoring (Coppola et al. 2020). The cloud fraction generally refers to an entire scene (or region of interest around the volcano) and is not necessarily indicative of the conditions just above the heat source. Figure 9a shows an image of the Sabancaya volcano acquired under conditions of almost completely clear skies. No thermal anomalies are detected by the SWIR channels of Sentinel 2. In reality, the image was acquired in concomitance with an explosion and a moderate-sized ash plume was covering the hot lava dome inside the crater. In this case, the absence of the anomaly is to be attributed to the plume and not to the cessation of thermal activity. This interpretation would be impossible based only on the time series of the data (without images) from which the doubt about the effective persistence of volcanic activity would always remain. The opposite case (Fig. 9b) occurred above the Kliuchevskoi volcano on May 2020, where a lava flow, emerging from the high-altitude central crater, was surrounded by clouds. The cloud fraction of this scene is greater than 80% although the thermal anomaly is completely visible and unaffected by clouds. An automatic classification algorithm based on cloud fraction of the scene would probably misclassify this data from the time series which instead is important to keep. The visual analysis and skimming

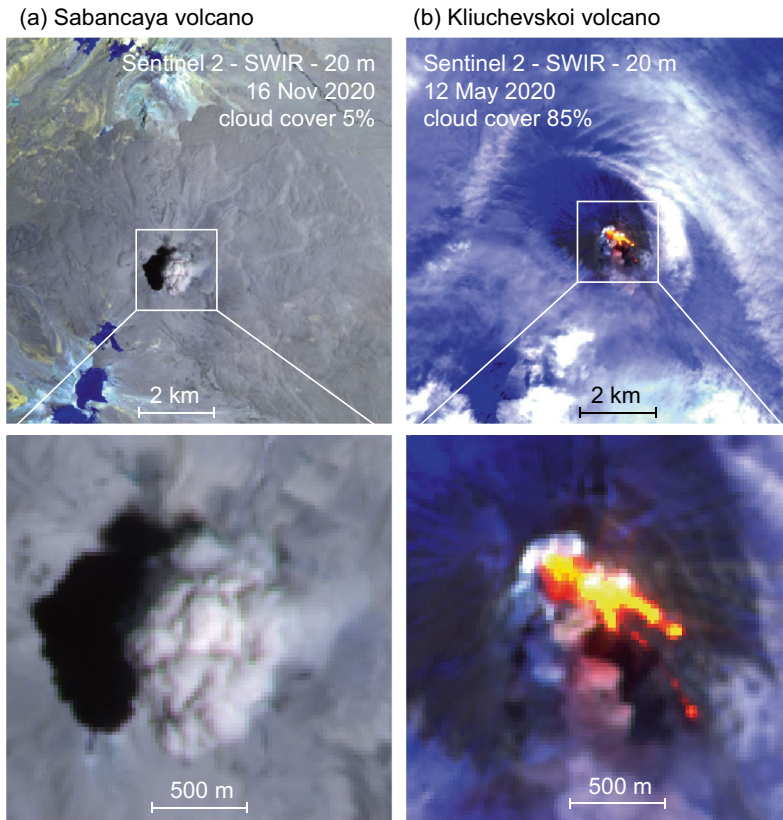


Fig. 9 **a** Sentinel 2 image acquired on Sabancaya volcano (Peru) on 16 November 2016 (band combination 8–7–6). The image is acquired in clear sky conditions (cloud cover < 5%) and no thermal anomalies are detected (high panel). The visual analysis of the crater area (bottom panel) reveals that the absence of thermal anomalies is possibly due to the presence of an ash plume masking the active lava dome. **b** Sentinel 2 image acquired on the Kliuchevskoi volcano (Kamchatka) on

12 May 2020 (band combination 8–7–6). The image is acquired in cloudy conditions (cloud cover > 80%) but a thermal anomaly in the summit area is detected by means of SWIR channels (top panel). The thermal anomaly is surrounded by clouds which, however, do not alter its detection. These two examples show how the use of simple cloudy indices (number of cloudy pixels within an image) can misrepresent the goodness of a thermal observation

of the images, based on the visibility conditions “above the thermal source”, remains one of the most effective methods for supervising thermal datasets, especially for sensors with low to moderate temporal resolution. On the other hand, supervising each image will be increasingly difficult and inconvenient considering the growing amount of satellite data to be analysed. Machine learning and artificial intelligence techniques are probably the most effective solution to automatically detect and classify hotspots and local clouds/plumes on large multispectral

datasets but they require a long learning phase that includes as many conditions as possible (Corradino et al. 2020, 2022).

4.1.2 Instrument Viewing Geometry

Satellite viewing geometry is another important factor to consider when dealing with thermal datasets. In the case of thermal anomalies within deep craters, the zenith of the satellite strongly influences the ability to observe any anomaly located on the crater floor. The VTF can be shadowed by the crater walls and the thermal

flux becomes conditioned by the viewing angle which introduces noise in the time series (Harris 2013). The satellite azimuth is also important to be evaluated when lava flows emplace along steep slopes. An example is the 2002 effusive eruption of Stromboli volcano (Italy) during which a lava flow descended along the Sciara del Fuoco (SdF), a steep collapse sector facing NW (Calvari et al. 2005; Fig. 10). The VRP measured by MODIS during the entire eruption is shown in Fig. 10a where it is possible to notice how the general trend of the thermal flux is affected by a noisy component, caused by the changing cloud cover and by the variable satellite viewing geometry. In fact, due to the specific position of the lava flow (within the SdF facing NW; Fig. 10b), all the MODIS observations from NW (i.e. favourable to the SdF) measured

a VRP higher than the observations from SE. The difference becomes more and more remarkable as we consider acquisitions with ever higher zeniths (Fig. 10c).

During effusive eruptions it is therefore always useful to take into account the actual satellite viewing angle (both azimuth and zenith) towards the lava flow, to assess whether the specific morphology of the volcano can (partially) mask the view of the thermal anomaly.

4.1.3 Wildfires

Wildfires can cause thermal anomalies that can be mistaken for volcanic activity. Although the use of machine learning techniques is giving promising results in the unsupervised classification of thermal hotspots of various origins (Kato et al. 2021), this distinction is still not applied

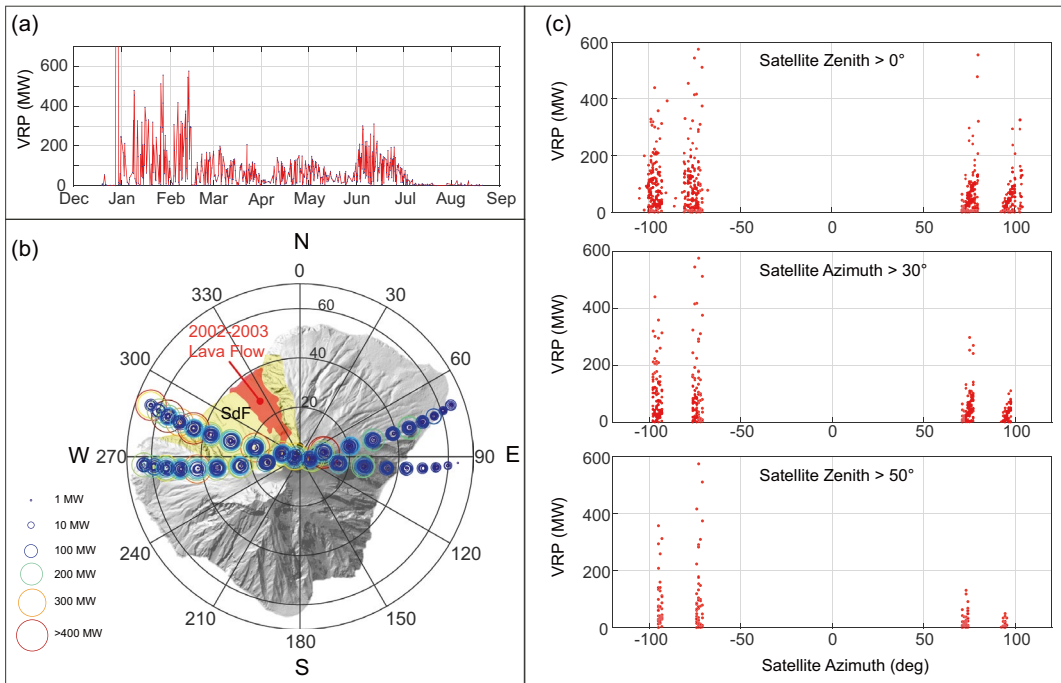


Fig. 10 **a** Timeseries of VRP recorded during the 2002–2003 eruption of Stromboli volcano (Italy) by the MIROVA system (data from Coppola et al. 2012). **b** Polar plot showing the intensity of VRP related to the satellite zenith and azimuth. The circle dimension and colors are proportional to the VRP. On the background is the shaded relief map of Stromboli showing the 2002–2003 lava flow emplaced along the Sciara del

Fuoco (SdF); **c** Correlation between the VRP and the satellite azimuth for three classes of satellite zenith (upper panel $>0^\circ$; middle panel $>30^\circ$; lower panel $>50^\circ$). The highest detections (>200 MW) occurred principally for satellite azimuths favourable to the lava flow emplacing along the SdF (from W-NW). A general reduction of VRP occurs when the observations are from E-SE, especially when the zeniths are high

in near real time. From a spectral point of view, wildfire are quite similar to high temperature VTF but can be recognized based on their location and/or through information on the ground. An exemplary case of potential misinterpretation occurred during the final stages of the 2018 eruption of Kilauea. On 5 August 2018 (at 23:45 UTC) the MODIS-MIROVA system detected a thermal anomaly on the northern edge (few km) of the Kilauea caldera (Fig. 11a). This anomaly was the first recorded on the summit area of Kilauea after the disappearance of the lava lake occurring three months before, in early May 2018, concurrently with the large caldera collapse (Fig. 11b). The collapse was associated with a large dike intrusion along the lower east rift zone (LERZ) that, in the following months, fed a large effusive eruption (Neal et al. 2019). This lateral eruption produced evident thermal anomalies detected by MODIS for the whole period, until 4 August when the eruption suddenly finished (Fig. 11c). Notably, the reappearance of thermal anomalies in the summit area (on 5 August) occurred just one day after the rapid decline of LERZ effusive activity, suggesting a possible link between the end of the lateral activity and the reappearance of a central activity (Fig. 11). Only in-situ observations made it possible to promptly verify that the summit anomaly was associated with a large brush fire that occurred just north of the collapsed crater (Patrick M., personal communication). This example demonstrates that extreme caution must be used in interpreting any thermal anomaly as the start of a new eruptive phase.

4.1.4 False Alerts

Each hotspot detection system is characterized by a percentage of false alerts, due to non-optimal algorithm performance, bugs in the acquired images, or extreme environmental conditions.

By comparing three of the most commonly used AVHRR-Class sensor based algorithms (VAST, MODVOLC, RST) Steffke et al. (2011), found false alert rates of ~21%, ~3% and ~6% respectively. Similar percentages were also obtained for MIROVA (~5%; Coppola et al. 2016) and for algorithms based on TM-Class

sensors such as S2PIX (2–14% including fires; Massimetti et al. 2020) and NHI tool (~15% including fires; Marchese and Genzano 2023). Usually, the effectiveness in detecting small thermal anomalies is inversely proportional to the number of false alerts. It is good practice to consult the user guides of each algorithm (if available) to better interpret the possible presence of false alerts and their origin. In general, however, false alerts of this type occur randomly (in space and time), making them easily recognizable even through the supervision of the images themselves.

4.2 Filtering the Time-Series

The supervision of the data allows filtering of the time series, reducing the noise, thus obtaining a trend that best reproduces the actual thermal emission of the observed phenomena. This step, in addition to highlighting the real trends of the activity in progress (and not due for example to a period of bad weather), allows scientists to obtain second level products such as the calculation of the Time Averaged lava Discharge Rate (TADR) and erupted volume (see next section). In addition, there is often the need to faithfully reconstruct the trend of thermal flux over time (essentially the VRP) and integrate the latter to obtain the total radiant energy released during an eruption.

The example shown in Fig. 12 refers to the August–October 2015 eruption of Piton de la Fournaise, where the raw time series of VRP, obtained by the MODIS-MIROVA system, was supervised and filtered to reconstruct the actual eruptive trend (Coppola et al. 2017a). It can be observed that the manual supervision (red line) made it possible to distinguish “apparent reductions” in VRP, associated with bad weather in late September, from “real reductions”, associated with the terminal effusive pulses that occurred in late October (Fig. 12a). The effect of data selection is even more evident in the calculation of the cumulative Volcanic Radiant Energy (VRE, calculated through trapezoidal integration of the VRP; Fig. 12b), where the

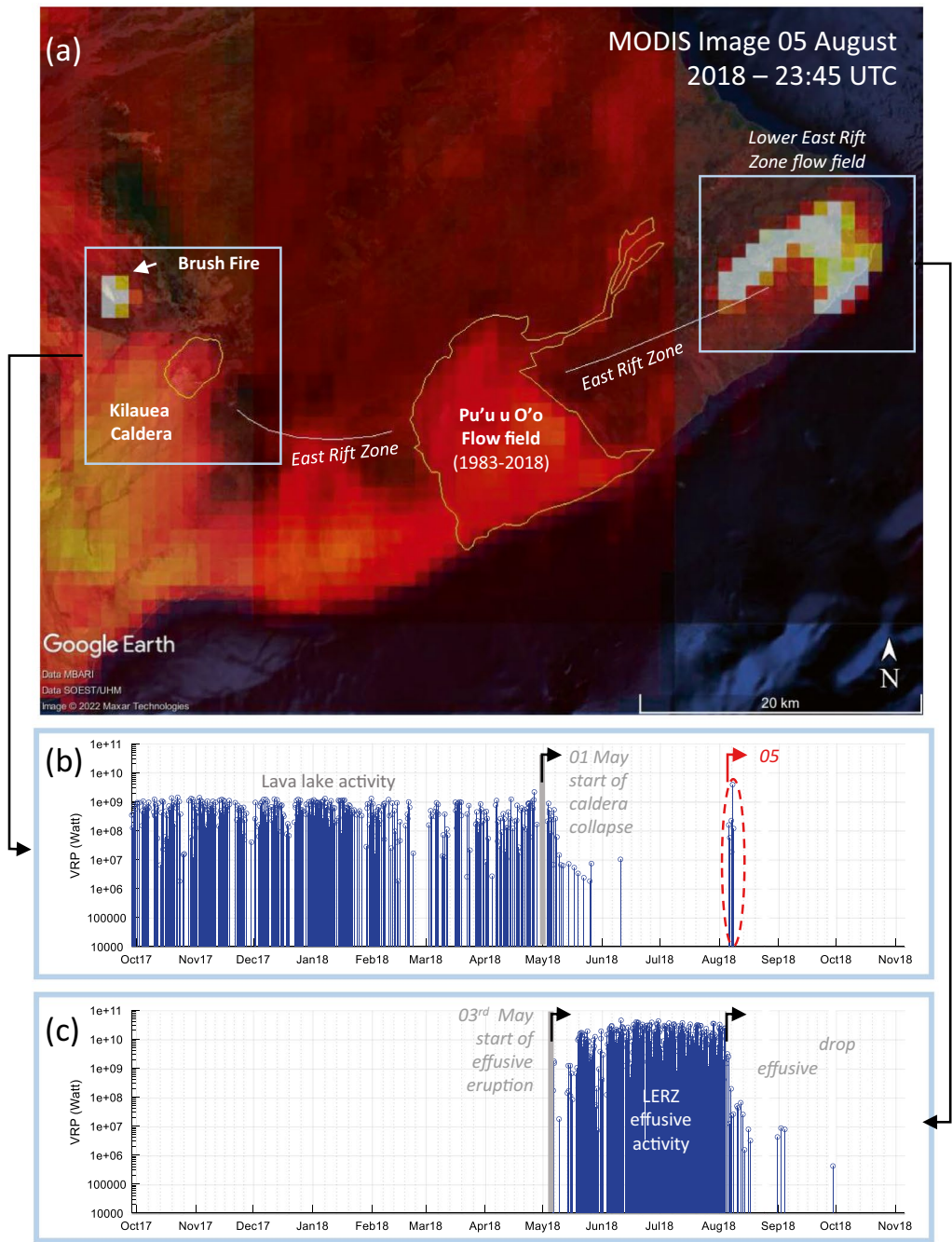


Fig. 11 **a** MODIS-MIR image acquired over Kilauea volcano on 5 August 2018 at 11:45 (UTC) and over-laid on a Google Earth image. Two main thermal anomalies were detected and related to (i) extensive lava flow along the LERZ and (ii) a bush fire, a few km NW of the summit caldera. This fire was initially misinterpreted as a potential thermal anomaly of volcanic origin. **b** Time-series of the VRP related to the summit area of Kilauea (left box in **a**). The anomalies until early May 2018 were due to the presence of the active lava lake inside

the caldera. The gray line indicates the beginning of the collapse that led to the disappearance of the lake. The anomalies reappeared in the summit area on 5 August, just after the abrupt end of the lateral effusion, but were linked to a bush fire; **c** time series of the VRP centered on the Lower East Rift Zone (LERZ- right box in **a**). These anomalies were due to the emplacement of a voluminous lava flow that persisted until 4 August, when the effusive activity suddenly drop

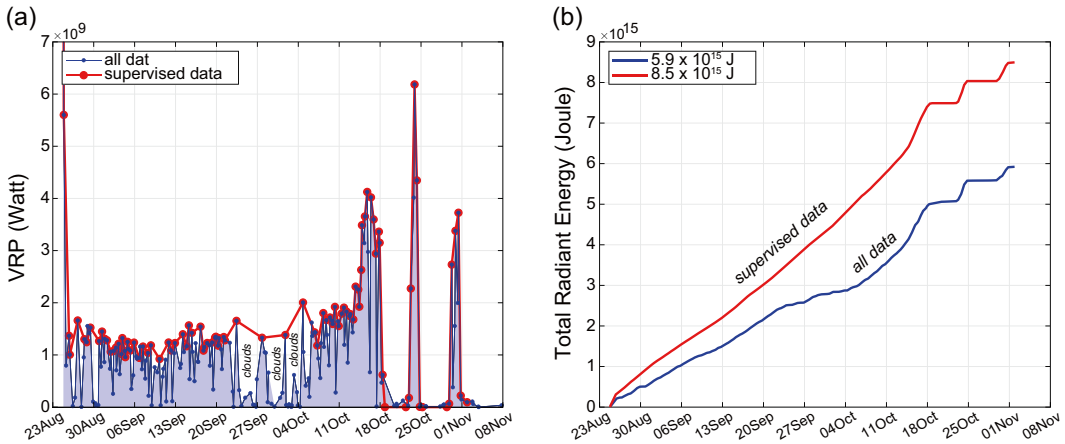


Fig. 12 **a** Timeseries of VRP recorded at Piton de la Fournaise during the August-October 2015 eruption (from Coppola et al. 2017a). Supervision of the images allowed 57% of the data to be discarded due to cloud

contamination or unfavourable viewing geometry. **b** Cumulated curves show an underestimate of ~30% of the total radiant energy when using all unsupervised data

supervised dataset provides energies ~30% higher than the unsupervised one.

4.3 Look at the Trend (at Different Timescales) Rather Than Single Data Points

The examples described above show that in the absence of images to support the thermal data, (i.e. by looking only at the time-series) a single data point does not necessarily provide useful information about the ongoing eruption, because some trend or pattern may become evident only on timescales of months or years. Furthermore, in some cases the cloud conditions or more generally the quality of the images is difficult to assess with certainty. For this reason, during an eruptive crisis it is often necessary to wait for further images/data to confirm/validate a trend/pattern that may become evident only at longer timescale.

The recent activity of the Santiaguito dome complex (Guatemala) provides a clear example in this sense (Fig. 13). For more than a century now this volcano has shown a

remarkable persistent eruptive activity, characterized by cyclic effusion of blocky domes and lava flows (Harris et al. 2002). The associated thermal activity has been detected for several years now (Fig. 13) and allows interpretation of the ongoing thermal release with the historical records (Massaro et al. 2022). For example, the MODIS image acquired on 18 February, 2022, in clear sky conditions (Fig. 13d) measured a VRP of 37 MW, suggesting a slight decrease in heat flux compared to the previous weeks, when a peak of 83 MW was recorded (Fig. 13a). However, looking also at the previous months, it is possible to realize that this last measure (37 MW) is still part of a general increasing trend which began as early as December 2021, and culminated around the beginning of February 2022 (Fig. 13b). This intensification was likely associated with the start of a new effusive cycle that produced a viscous flow along the NW flank, as detected by the Sentinel 2 image of January 2, 2022 (Fig. 13e). Looking at the dataset at an even larger time scale (more than 20 years; Fig. 13c), we realize that this new effusive cycle was preceded by a long “preparatory” phase, which saw both the VRP detected

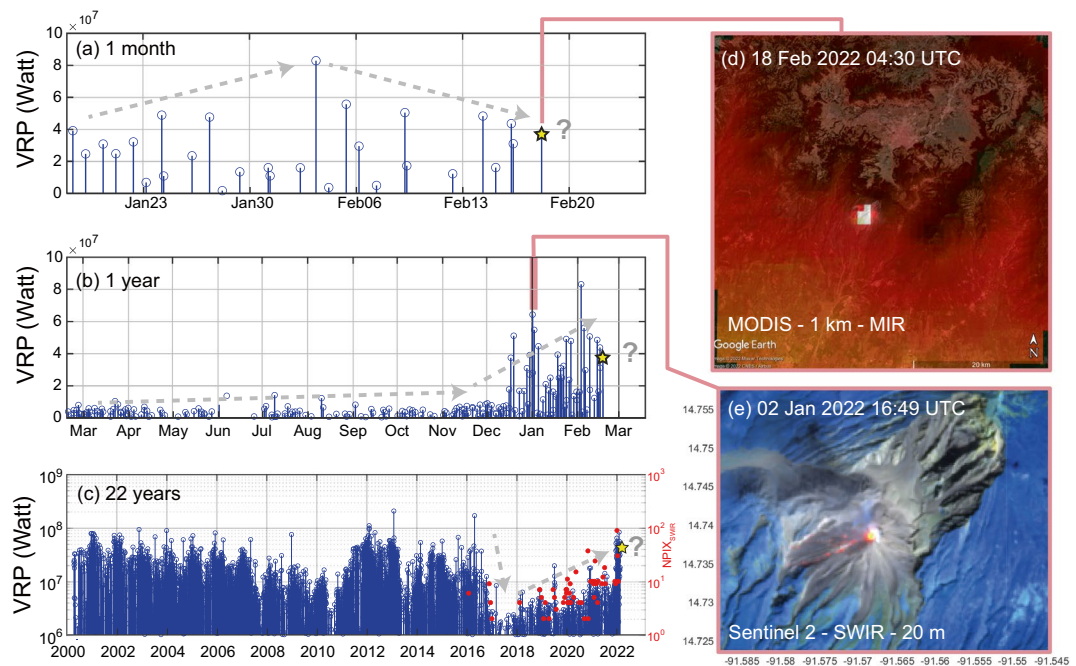


Fig. 13 Time series of the thermal flux (VRP) recorded up to 18 Feb 2022 at the Santiaguito dome complex (Guatemala) in three different time scales: **a** last month; **b** last year; **c** last 22 years. The yellow star indicates the last VRP measurement on February 18 (04:30 UTC) as measured by the MODIS sensor **d**. The gray arrows in the graphs indicate the general trend that is depicted on the basis of the data displayed on each respective time scales. While in recent weeks the VRP seems to decrease

(a), the analysis of the last year reveals that the volcano was in an elevated thermal regime that began in Dec 2021, likely associated to the emplacement of a new viscous lava flow on the southwestern flank **e**, as detected by the Sentinel 2 on 2 Jan 2023. The combined long-term analysis (c) of MODIS (VRP in blue) and Sentinel 2 ($N_{PIX,SWIR}$) data reveals that a gradual increase in thermal activity of this volcano had already begun in 2017

by MODIS and the number of hot pixels detected by Sentinel 2 (Massimetti et al. 2020) gradually increasing for more than four years (at least since 2017; Fig. 13c). Furthermore, the comparison with this historical data allows evaluation of the peak VRP reached on February 2022 which is compatible with peaks of previous cycles of effusive activity of this volcano (~100 MW; Massaro et al. 2022). A useful practice is therefore to compare the values acquired in real-time with the historical time series (if available). The Landsat, MODIS, and ASTER data now make it possible to have decades-long time series, potentially available for this type of comparative analysis.

5 Part III: Second-Level Products: Time Averaged Lava Discharge Rate (TADR), Lava Lake’s Level (h_{lake}), Crater Lake’s Temperature (T_{lake})

A series of second-level products can be obtained and distributed starting from the thermal data processed in NRT and possibly supervised. These products require additional parameters which are generally assumed or settled by an expert based on previous calibrations or observations. For this reason, the second-level products are seldom distributed automatically

(as can be done for the N_{PIX} , VRP, etc., parameters) but require one or more assumptions and continuous supervision and interpretation of the phenomena in progress. In the next sections I will give some examples on how to obtain, three types of second level products starting from radiance or VRP data.

5.1 Hazard Monitoring During Effusive Eruptions: Time Averaged Lava Discharge Rate, Erupted Volume, and Lava Flow Length

The *TADR* is among the most useful parameter to be estimated during an effusive eruption since it provides the average volumetric output rate of lava in the hours/days preceding the acquisition of the satellite image (Harris et al. 2007a, b).

The approach to estimating the *TADR* from satellite thermal data originated in the 1980s and is based on the work of Pieri and Baloga (1986) who found a direct proportionality between lava discharge rate and the surface area of the resulting active lava flow. Starting from this relationship satellite-based *TADR* was initially estimated by applying the method from Harris et al. (1997; 2000), later revised by Wright et al. (2001), according which:

$$TADR = x \bullet A_{hot} \quad (18)$$

where A_{hot} is the active area of the lava flow (retrieved from Eq. 13) and x ($m \ s^{-1}$) is an empirical parameter that embeds all the thermodynamic conditions assumed for the studied *TADR*-Area relationship (Harris and Baloga 2009). Equation 18 is commonly applied to TIR radiance data, by calculating A_{hot} from Eq. 15 and by assuming a range of T_{hot} spanning from 100 to 500 °C (generally ascribed to the cool and hot model, respectively; see Harris and Baloga 2009). The value of x is assumed on a case-by-case basis after previous calibration. In these cases, the thermal approach provides values of lava discharge time averaged over several days before image acquisition (cf. Fig. 4b).

An alternative method, based on VRP values, was proposed by Coppola et al. 2013, according which:

$$TADR = \frac{VRP}{c_{rad}} \quad (19)$$

where c_{rad} is again an empirical coefficient describing the efficiency of a lava body to change its area and/or to insulate its inner core, in response to a given *TADR*. It was found that c_{rad} is strongly controlled by the rheological properties of the emplacing lava (Coppola et al. 2013), with values decreasing from basic ($1-4 \times 10^8 \ J \ m^{-3}$) to intermediate ($1.5-9 \times 10^7 \ J \ m^{-3}$) and acidic compositions ($0.2-1 \times 10^7 \ J \ m^{-3}$). On this basis, an empirical relationship has been proposed to derive the c_{rad} of an active lava flow, based on the silica content (X_{SiO2} in wt%) of the erupted lava.

$$c_{rad} = 6.45 \bullet 10^{25} \bullet (X_{SiO2})^{-10.4} \quad (20)$$

Since the VRP is based on the excess of MIR radiance (see Eq. 17), this method provides discharge rate values averaged over 6 to 24 h before the acquisition of each image (cf. Fig. 4b) thus a shorter time interval than method 1.

Both the methods described above depend on the excess of radiance (ΔL) and can be reconciled by a simple third approach, named “direct conversion” after Verdurme et al. (2022), according to which:

$$TADR = m_{\lambda} \bullet \Delta L_{\lambda} \quad (22)$$

where m_{λ} represents the wavelength-dependent coefficient at the base of the direct relationship between lava-effusion rate and spectral radiance. The coefficient can be directly retrieved from Eqs. 18 and 19 or from linear regression of independent data (Harris et al. 2007a, b; Coppola et al. 2009; Kaneko et al. 2019, 2021) and depending on the wavelength used provides *TADR* values averaged over different time windows (Fig. 3). For example, Kaneko et al. (2021) recently applied this approach to estimate *TADR* using nighttime Himawari-8 SWIR (1.6- μm) infrared data. As the 1.6- μm band is preferentially sensitive to high-temperature,

young surface (but is insensitive to medium and low-temperature areas; Fig. 4), the anomaly is thought to reflect the effusion of incandescent lava near the vent. In this case, the time window considered is probably less than a few hours (Fig. 4b) and is closely related to an “instantaneous effusion rate” rather than time-averaged discharge rate (Kaneko et al. 2021).

Whichever approach is used, the calculation of lava discharge rate is generally carried out during an effusive crisis to monitor the emplacement of lava flows (Harris et al. 2016a and reference therein). In particular, the prompt estimation of *TADR* allows for the setup of flow propagation models that forecast the areas potentially at risk of lava inundation (Wright et al. 2008; Del Negro et al. 2015; Chevrel et al. 2022; Harris et al. 2016b).

Numerous are the applications carried out during the recent eruptions of Etna volcano, where the satellite thermal data are routinely used to drive real-time simulations of lava flow path and length (Del Negro et al. 2008; Vicari et al. 2008; Ganci et al. 2012b; Cappello et al. 2018 among others).

On the other hand, this approach has only a few other operational examples in other basaltic

volcanoes (Harris et al. 2017, Tarquini et al. 2020, Cappello et al. 2016). In 2014, a coordinated international protocol has been developed to respond to the effusive crises of Piton de la Fournaise (Harris et al. 2017). Since then, the protocol has been used for all eruptions and involves the integration of satellite-derived *TADR* into probabilistic and thermo-rheological models, to predict areas flooded by lava and their length (Harris et al. 2019; Chevrel et al. 2022). Operationally, this procedure allows for the production of lava flow hazard maps (see also Chevrel et al. this issue), shared with the local civil protection within a few hours from the beginning of each eruption.

In addition to *TADR*, satellite-derived thermal data are increasingly used for tracking lava flow’s advancement and identifying the active portions of a lava field. In this regard, the recent eruption of the Wolf (Galapagos) highlights the role of satellite thermal imagery in monitoring remote volcanoes with sporadic in-situ field observations (Fig. 14). The Instituto Geofísico y Escuela Politécnica Nacional (IGEPN), in charge of monitoring the Galapagos volcanoes, uses the MIROVA and FIRMS platforms (Table 2) to track the activity of Wolf and to compare

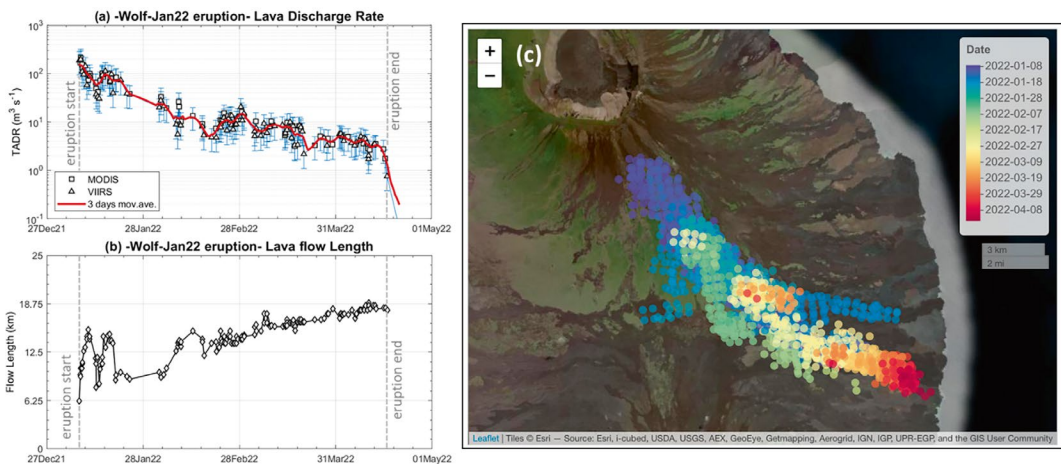


Fig. 14 Evolution of the 2021 effusive eruption of Wolf Volcano inferred from satellite thermal data. **a** Timeseries of *TADR* retrieved by MODIS and VIIRS data elaborated through the MIROVA algorithm, and delivered via email to the Insituto Geofísico y Esquel

Politécnica Nacinal (IGEPN). **b** Timeseries of the lava flow length as retrieved from MODIS and VIIRS data, **c** Space–Time evolution of the lava flow field, derived from FIRMS thermal alerts elaborated by Vasconez et al. (2022)

the thermal anomalies detected by satellite with other parameters, such as the seismicity and outgassing. On 7 January, 2022, at 05:20 (local time) a new eruptive fracture opened on the southern flank of the Wolf volcano. A few hours later, at 07:18 UTC a VIIRS image detected a ~6 km long thermal anomaly on the south flank, associated with an advancing lava flow (Fig. 14). Since that time MIROVA data were used to inform IGEPN and infer the effusion rate trend for short to midterm forecasts (Fig. 14a). At the same time the daily mapping of thermal anomalies (Vasconez et al. 2022), allowed the observatory to follow the position of the active front (Fig. 14b) and to map the spatio-temporal evolution of the flow field and the possible opening of ephemeral vents upstream (Fig. 14c).

The time-trend analysis of effusion rates may be also used to decode eruptive mechanisms (e.g. pressurized vs. steady-state eruptions; Wadge 1981; Harris et al. 2000) and has proved fundamental in predicting the end of some eruptions (Bonny and Wright 2017; Coppola et al. 2017b). Effusion rate trend modelling can also be used to predict the final erupted lava volume (Tarquini et al. 2019), or to recognize time-predictable vs. volume predictable patterns over decade-long time series (Coppola et al. 2021).

5.2 Tracking the Level of Lava Lakes (h_{lake})

Lava lakes are one of the rarest and most interesting volcanic manifestations on earth. Nevertheless, they pose a danger to the populations living on their slopes because they constitute a reservoir of molten magma suspended at high altitudes, which can be dramatically drained during lateral eruptions. The recent eruptions of volcanoes hosting long-lived lava lakes, such as Erta Ale in 2017 (Moore et al. 2019), Ambrym in 2018 (Hamling et al. 2019), Kilauea in 2018 (Neal et al. 2019), and Nyiragongo in 2021 (Boudoire et al. 2021) have shown that the lateral intrusion of dikes and the eventual opening of low altitude vents, can “drain” the central magmatic column (and the

lava lake itself) by generating large rapid lava flows. It has been shown that the level reached by a lava lake is closely related to the pressure conditions inside the magma chamber so that the lava lake itself acts as an efficient “piezometer” (Patrick et al. 2019). It is therefore clear that the monitoring of the lake level is fundamental to evaluating the hazard and the potential impact of an effusive draining event (Burgi et al. 2014, 2020).

Lava lakes are usually contained in craters whose shape can be modelled as an inversed truncated cone (Burgi et al. 2014). According to this model, the lava lake level (h_{lake}) can be expressed as:

$$h_{lake} = \frac{d_{lake} - d_0}{2 \cotan(\gamma)} \quad (23)$$

where d_{lake} is the lake diameter (m), d_0 is the diameter at the base of the truncated cone, and γ is the angle of the inner walls of the cone to the horizontal (Burgi et al. 2020).

By inverting Eq. 16, and using the *VRP* as a measure of the radiant power emitted by the lake’s surface, we can then calculate the diameter of the lake as:

$$d_{lake} = \sqrt{\frac{VRP}{\sigma \varepsilon (T_e^4 - T_{bk}^4)}} \quad (24)$$

In practice, by combining the Eqs. 23 and 24, and after calibration of γ , d_0 and T_e , it is possible to calculate the level of a lava lake starting from the measurement of *VRP*, as illustrated in the case of Nyiragongo (Fig. 15). The 20-years-long evolution of satellite-derived h_{lake} is consistent with the general level measured on the ground (Burgi et al. 2014 and 2020), although the apparent smaller-scale fluctuations are attributable to changes in the cloud fraction (the data presented in Fig. 15 were not supervised). Some peaks of *VRP* (Fig. 15a) are likely unrelated to sudden rises of the lake level of hundreds of meters (Fig. 15b), but are likely related to the occurrence of overflows above the crater terraces or the opening of a new vent(s) inside the crater, as occurred in October 2016 (Valade et al. 2018). On 22 May 2021, a dramatic

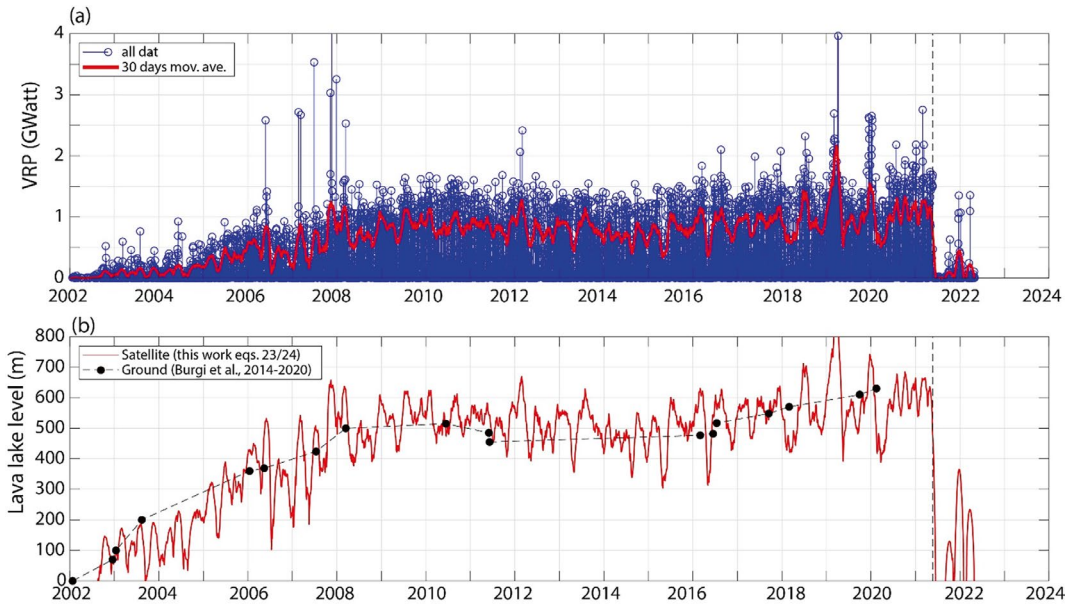


Fig. 15 **a** VRP time-series recorded at Nyiragongo volcano which between 2002 and 2021 hosted one of the most active lava lakes in the world. The lake was drained during a dramatic lateral eruption on 22 May 2021 (dashed line). **b** Lava lake level (red line) is derived from thermal data (Eqs. 23 and 24) by assuming

the geometrical parameters given in Burgi et al. 2014: $2\cotan(\gamma)=0.38$, and $d_0=43$ m. The T_e and T_{bk} are assumed constant throughout the whole period and equal to 1000 K and 280 K, respectively. For comparison the lava lake level measured on the field is shown by black points (data from Burgi et al. 2014 and 2020)

eruption (grey dashed line in Fig. 15) sees the opening of an eruptive fracture on the southern flank of the volcano (Boudoire et al. 2021). This event completely drained the lake and generated a rapid lava flow that invaded the city of Goma (Smittarello et al. 2022).

This approach requires specific calibrations based on the knowledge of the crater morphology (γ and d_0), as well as an assumption of the effective temperature of the lava lake (T_e). Episodes of lake emptying and/or collapse of the crater or caldera can strongly alter the shape of the crater so that after each drainage episode it is essential to recalibrate the model. In the case of Nyiragongo (Fig. 15), the thermal anomalies recorded after the 2021 eruption, which completely drained the lake, are likely to be associated with an intermittent reappearance of magma on the bottom of the crater. Under these geometrical conditions, the model fails and need to be recalibrated based on an updated crater morphology.

On the other hand, it is also true that the temperature of the lava lakes can vary with time, depending on the rate of magma convection, the quantity of gas flux, and the size of the lake (Lev et al. 2019, Campion and Coppola 2023). These parameters can change with time, or from lake to lake, making the effectiveness of the model subject to the assumption of an appropriate lava lake dynamic.

5.3 Monitoring the Temperature of Intra-Crater Lakes (T_{lake})

Of the 400 volcanoes that have erupted in the last 100 years, at least 60 host intra-crater lakes (Rouwet et al. 2015). Intra-crater lakes are a very common feature in a volcanic environment representing the intersection of volcanic, hydrothermal, and degassing processes of the underlying volcano (Christenson et al. 2015). Intra-crater lakes display long-term trends,

seasonal cycles and short duration bursts of activity that can be tracked from space, since the area, temperature and color of the water bodies can be measured by satellites (Murphy et al. 2018; Caudron et al. 2018).

Thermal monitoring of volcanic lake waters is fundamental for assessing volcano-hydrologic hazards (Manville 2015). It allows researchers to track the flux of the gases emitted by submerged fumaroles and determine the energy that is entering the bottom of the lake from the volcano (Rouwet et al. 2014; Rouwet and Morrissey 2015). Many volcanic lakes have been found to suffer from cyclical heating episodes, possibly associated with deeper magmatic processes or periodic instabilities in the hydrothermal system (Werner et al. 2006). These cycles occur with variations in water temperature and are commonly associated with volcanic earthquakes (Rouwet and Morrissey 2015). From the satellite thermal point of view, the measurement of the water temperature is normally carried out using TM-class sensors equipped with TIR bands (such as ASTER and Landsat) that have pixel sizes smaller than the lake and can accurately measure the water temperature, even with a few degrees of variations (Oppenheimer 1993; Trunk and Bernard 2008). Nevertheless, thanks to the increased sensitivity of the new generation of AVHRR-Class sensors (e.g. VIIRS, Sentinel 3; Table 1) these instruments can

be used for the same purpose but with the advantage of a higher temporal resolution. In this case, where (the pixel size is larger or comparable to the lake size), the simplest approach is to assume a dual-component mixture problem, according to which the spectral radiance coming from a lake of area A_{lake} and temperature T_{lake} is given by:

$$L_{lake}(\lambda, T_{lake}) = L_{bk}(\lambda, T_{bk}) + \left(\Delta L_{tot}(\lambda) \cdot \frac{A_{pix}}{A_{lake}} \right) \quad (25)$$

Here, $L_{bk}(\lambda, T_{bk})$ is the background radiance, ΔL_{tot} is the total excess of the radiance of the anomalous pixel(s) imaging the lake (see Eq. 12), and A_{pix} is the pixel area. The temperature of the lake can therefore be obtained by inverting Planck's law (Eq. 6). This simple approach was applied to the VIIRS data (imaging bands at 375 m) acquired at the Ruapehu volcano which hosts an intra-crater lake of about 0.2 km² (measured on Google Earth) inside the summit crater. The data were processed using the MIROVA algorithm (Fig. 16) in search of any image where the lake had a sufficient temperature contrast compared to the background, making it possible to measure ΔL (MIR) and L_{bk} (MIR). The radiance obtained from Eq. 25, converted into temperature (Fig. 16) are in excellent agreement with the data measured directly on the lake surface (available on

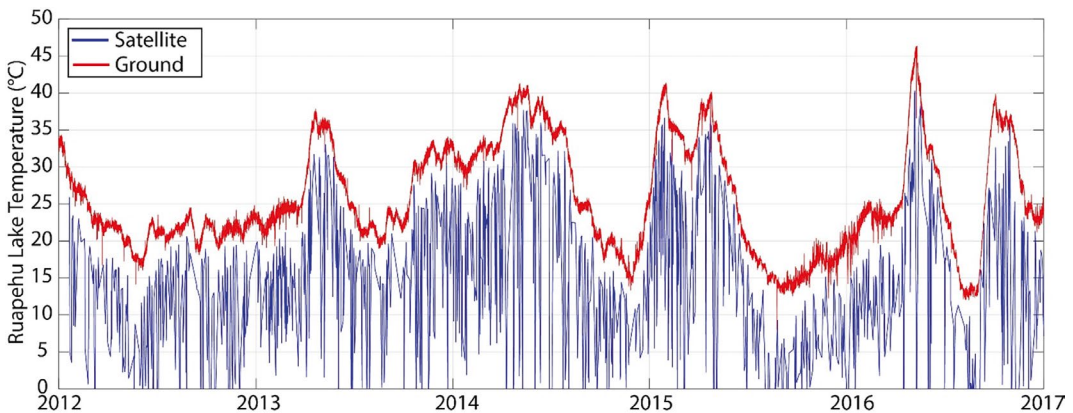


Fig. 16 Evolution of the Ruapehu's crater lake temperature between 2012 and 2017. The blue line is obtained from VIIRS data by applying Eq. 25 ($A_{lake}=200,000$

m²; $A_{pix}=140,625$ m² (375×375 m); the red line corresponds to the temperature measured on site (available on <https://www.geonet.org.nz/data/tools/FITS>)

<https://www.geonet.org.nz/data/tools/FITS>), although a shift of a few degrees is visible, likely associated with the lack of atmospheric correction for the satellite data. The result shown in Fig. 16 underlines how the basic treatment of the “excess of radiance (ΔL)” is extremely effective for monitoring the frequent heating cycles of Ruapehu crater lake also in absence of appropriate atmospheric corrections.

However, two assumptions are necessary for this approach to provide good results. The first is that the temperature and the size of the lake must be adequate to produce an “excess of radiance” measurable by space-based sensors. The second assumption is that the size of the lake (A_{lake}) must remain constant over time. In some cases, the size of the lake can change very quickly making Eq. 25 useless.

6 Conclusions

Currently, there are at list 12 infrared sensors aboard operational satellites (polar or geostationary) that are used for volcano thermal monitoring (Table 1). These systems (combination of platform plus sensor) have different spatial, spectral, and temporal characteristics that allow observation of a wide range of volcanic phenomena at very different spatial and temporal scales. Numerous algorithms have been developed by various groups to automatically detect and quantify the heat sourced by the volcanic thermal features (VTF). Together with web-tools that allow the vision of some infrared images stored in the cloud, some of these algorithms currently run in NRT to constitute the state of the art of automatic volcanic hotspot detection systems. The wide availability and variability of operational tools available on the web (Table 3) now make it possible to detect volcanic phenomena at different spatial and temporal scales, such as the slow appearance of small ($< 1 \text{ m}^2$) fumaroles, fast emplacement of large ($> 10 \text{ km}^2$) lava flows or pyroclastic density currents. Nevertheless, there is currently no automatic

system capable of tracking any type of VTF so exhaustive monitoring can only take place using a multi-sensor approach.

Precisely because of the different characteristics, each system can provide information on the current volcanic activity using different metrics. Some of these metrics (such as the number of pixels or the pixel integrated temperature above the background) are basic and only provide a proxy of the thermal activity in progress. Others (the excess radiance or the volcanic radiative power) are more quantitative and can be used to obtain more understandable information, like the area of the VTF, its radiating temperature, or the combination of the two, that is the radiant power.

During pre-eruptive crises or ongoing eruptions, it is a good practice to view and interpret any thermal data detected by satellite, especially to evaluate the possible effect of clouds, unfavourable viewing conditions, and the occurrence of any false alerts. This supervision allows production of second-level products, such as the Time Average lava Discharge Rate (TADR), which, after ad-hoc calibrations, can be incorporated into lava flow models useful for mitigating the risks associated with lava flows. Similarly, the monitoring of the level of lava lakes, or the temperature of an intra-crater lake, can be carried out after a calibration of the respective models, being understood that these second-level products are valid only within the limits of the assumptions underlying the models themselves.

In general, satellite thermal monitoring has reached a level of maturity that can be considered in the same way as more conventional monitoring systems (seismicity, degassing, deformation). In particular, infrared data acquired by satellites allow a detailed quantification of the “surface” activity which can be difficult to assess especially in hard-to-reach volcanoes. The integration of this information with other commonly measured parameters certainly constitutes an added value to monitoring and understanding the large variety of phenomena occurring during eruptions.

Acknowledgements I want to thank Ian T.W. Flynn and an anonymous reviewer, for thorough review of the first draft and for the constructive suggestions that have assisted in greatly improving and completing this work. I thank F. Marchese, for having provided the SEVIRI data from Mt. Etna, K. Reath, for providing the ASTER data of Sabancaya and B. Bernard, for sharing the Wolf's map of thermal anomalies. This work was made possible thanks to the help of M. Laiolo, F. Massimetti, A. Campus, S. Aveni and many other collaborators who have allowed the maintenance and continuous development of the MIROVA system.

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From Eruptive Histories to Volcano Monitoring: Probabilistic Eruption Forecasting and Volcanic Hazard Assessment at Varying Temporal and Spatial Scales

Laura Sandri, Pablo Tierz, and Susan C. Loughlin

Abstract

In this chapter, we introduce the reader to the concepts of quantitative eruption forecasting and volcanic hazard assessment. These are two key tasks that modern volcanology increasingly tackles by means of probabilistic approaches, in order to account for the different types and sources of uncertainty that affect both volcanic processes and our knowledge of them. We detail how these two tasks are accomplished at different temporal scales from the short- to the long-term, based on different pieces of information, and using a variety of statistical models and approaches. Such models and approaches are also relevant for volcanic hazard assessments at varying spatial scales, spanning from a local, single-volcano scale to more comprehensive assessments of hazard from multiple volcanoes. We

describe how different factors are accounted for in the available literature, in terms of monitoring data, eruption size or style, vent location, and volcanic phenomena (such as tephra fallout, ballistic ejection, gas dispersal, pyroclastic density currents, lava flows and lahars). Future developments in the area may revolve around: (i) tackling data scarcity through creating and maintaining harmonized (global) volcanological databases, combined with the use of analogue volcanoes; (ii) further developing frameworks to test, validate and/or compare physical and statistical models in order to optimize their application to probabilistic volcanic hazard assessment and eruption forecasting; (iii) harmonization of data formats and data structures to enable scaling of hazard and risk assessments across hazardous phenomena and sectors of society.

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1 Introduction

The understanding of volcanic hazard and risk is one of the key goals of modern volcanology (UNISDR 2015; Loughlin et al. 2015; Murnane et al. 2016). Although we focus on quantitative hazard assessment methods here, these can be combined with semi-quantitative and qualitative approaches to better understand potential impacts, risks and to support risk management and risk reduction. Common understanding of

hazard and risk enables effective coordinated and collaborative contributions to the mitigation and reduction of risk. For natural events, risk (R), is generally defined (Fournier d'Albe 1979), as: $\text{Risk} = \text{Hazard} \times \text{Value} \times \text{Vulnerability}$.

Hazard is usually defined as the probability of a given hazardous volcanic event to impact a given point in space, within a specific time window, with an intensity above a given threshold: a “volcanic” example could be the hazard from tephra loading on a roof, e.g., the probability of accumulating more than 300 kg/m² (a threshold critical for roof collapse or serious damage for several types of roofs, Jenkins et al. 2014) of tephra in a given area or on a given critical infrastructure (such as a hospital) in the next 50 years. Value is defined as the amount of people, buildings or assets that may be impacted by the volcanic hazardous event. In volcanology (e.g., Newhall and Hoblitt 2002), it has often been replaced by the Exposure, defined as the probability that the people or property of concern would still be at the dangerous location at the time of the impact of the hazardous volcanic event. This slight difference between Value and Exposure is made to better acknowledge the effect that mitigation measures, such as evacuations, have in risk reduction: Exposure is drastically reduced as evacuations are called and carried out, and, consequently, so does Risk. Exposure data may comprise site-specific information such as building or roof footprint, gridded data at different resolutions, or aggregated data such as administrative regions. Different exposure models are used for different assets, including temporal and spatial variability (e.g. building occupancy through a day or season). Vulnerability has been previously defined as the proportion of the Value which is likely to be lost as a result of a given event (Fournier d'Albe 1979), but can also be treated as the probability that a given level of damage in an asset (equal to or lower than the ‘total loss’), is exceeded due to a given hazard intensity being experienced by the asset (e.g. Selva 2013; after Douglas 2007).

Vulnerability and fragility may be assessed using vulnerability and fragility functions that relate hazard intensity to damage or failure (e.g. Zuccaro et al. 2008; Jenkins et al. 2015a), as well as indicators for different types of vulnerability (e.g. social vulnerability). Vulnerability functions describe the amount of damage/loss expected as a result of a particular hazard intensity, for example, physical vulnerability accounts for the likelihood of an exposed asset (e.g. a roof) to suffer damage/loss as a result of tephra loading; a fragility function describes the probability that damage to an asset will equal or exceed a damage threshold, given a specific hazard intensity. Social vulnerabilities are not necessarily linked to hazard intensities and may be described by a wide variety of indicators and indices that, among other aspects, describe the ability of exposed people/society to withstand stresses (e.g. Donovan et al. 2012; Pardo et al. 2015; Hicks and Few 2015).

Vulnerability and exposure are usually analysed mainly by engineers, sociologists and economists, while volcanologists currently mostly contribute to quantifying hazard. Nevertheless, volcanologists may also be well-placed to gather damage data which is severely lacking and hindering progress in risk assessment. In order to understand potential impacts and risk, trans-disciplinary collaboration between scientists, risk and emergency managers, and with those who may experience damage and loss, is essential. Volcanic hazard can have wide consequences and mitigating these also requires learning from past events and considering events and impacts that may occur in the future but have few precedents. In particular, volcanological knowledge, data and skills can help in quantifying (i) the probability of the occurrence of a volcanic eruption within a given time window (that we will refer to as “eruption forecasting” and that mostly relates to the source of volcanic hazard, i.e. the volcano studied) and (ii) the probability that, given an eruption at that volcano, a hazardous

phenomenon will ‘propagate’ and produce an ‘impact’ on its surroundings. The analysis of such probabilities involves many different parts and components, including the spatial probability of eruption occurrence (or vent opening), the probability of the size of the eruption and, of course, the probability that different hazardous phenomena (tephra dispersal and deposition, propagation and deposition of pyroclastic density currents—PDCs—and/or lava flows, etc.) impact different areas on and around the volcano studied. We will term Probabilistic Volcanic Hazard Assessment (PVHA, Marzocchi et al. 2010; Connor et al. 2015; Tierz 2020, and references therein) the ensemble of analyses aimed at calculating the aforementioned probabilities. We nevertheless note that PVHA can also be non-conditional on eruption occurrence, in which case the combined probabilities of different components of the hazard assessment (e.g. vent opening, eruption size, PDC inundation and/or all together) do incorporate the ‘eruption-forecasting term’, i.e. the probability of eruption occurrence, into the resulting PVHA (e.g. Marzocchi et al. 2008, 2010).

In this chapter, we will focus on eruption forecasting and volcanic hazard assessment. By nature, eruption forecasting and volcanic hazard assessment are probabilistic (as their definitions imply). We will first explain what long- and short-term mean in the context of volcanic hazard assessment. The partition between these two “regimes” is necessary as the data used in long- and short-term evaluations tend to be rather different (e.g. Marzocchi et al. 2008). Secondly, we will explain what types and sources of uncertainty have the largest importance when calculating eruption forecasts or hazard assessments. We will then go through the existing methods to carry out these tasks, dividing them into the two regimes of long- and short-term. We will also analyze the particularities of (probabilistic) volcanic hazard assessments at spatial scales from the single volcano to multi-volcano hazard assessments (regional to global). We will end the chapter presenting some concluding remarks and possible future directions in the field.

2 Long-Term Versus Short-Term in Volcanic Hazard Assessment

We often read and hear of “long-term” and “short-term” assessments and regimes, without a clear reference in terms of time units. In hazard assessment, this terminology refers to the temporal horizon over which we might expect significant changes in the status of the system studied (Newhall 1999; Marzocchi et al. 2008). Thus, in volcanology, the two temporal frames can be broadly divided into:

- Short-term referring to a rapidly evolving situation, i.e., typically an ongoing volcanic unrest (defined as a deviation from the ‘background behavior’ that a particular volcano usually displays) or eruption, during which we expect changes over the next hours, days or a few weeks, so a hazard assessment is focussed on such time frames; and
- Long-term referring to changes in the volcanic system over longer (even geological) timescales, so we may be typically interested in assessing the hazard over a year, decades or centuries.

The categorization is not only semantic, as (i) it is meant to answer different questions regarding the structure and functioning of the volcanic system, and (ii) it is based on different pieces of information. For example, while long-term hazard assessment is usually developed to evaluate long-term risk for land-use management purposes and planning, short-term assessments are a guide to manage risk during emergencies. Similarly, while in long-term hazard assessment, one mostly relies on the geological record, possible historical chronicles available, expert elicitation and forward modeling, in the short-term it is mostly the current monitoring data that guide the assessment, often supported by different approaches to inverse modeling.

In reality, this distinction is almost never ‘black-and-white’, but rather a ‘gray area’ in which the two types of information respectively

lose and gain weight in the hazard assessment. Also, different volcanoes can have significantly different timescales in terms of their magmatic and volcanic processes (e.g. Whelley et al. 2015), so even the long-term can differ by orders of magnitude across different volcanic systems (e.g. Selva et al. 2022). These differences between volcanic systems extend to their ‘lifetime cycles’, which can make the frequency, size and style of eruptions strongly inhomogeneous in time (e.g. Scott 1990; Davidson and De Silva 2000; Cioni et al. 2008; Naismith et al. 2019). Current practices for analogue-volcanoes selection (e.g. Tierz et al. 2019, 2021; Burgos et al. 2023) and/or volcanic hazard assessment (e.g. Sandri et al. 2012; Jenkins et al. 2012; Tierz et al. 2020; Hayes et al. 2022) tend to consider the current or a time-averaged stage or state only, with a few exceptions that consider a more ‘dynamic’ approach to the hazard assessment (e.g. Bevilacqua et al. 2016; Selva et al. 2022). In any case, both temporal scales in hazard assessment benefit from each other as: (1) monitoring data inform us about whether the volcanic system studied is more likely to be in unrest or in a background state (e.g. Marzocchi et al. 2008; Newhall and Pallister 2015); and (2) ‘long-term data’, such as forward modeling, can become invaluable to update PVHA for hazardous phenomena in the short-term (e.g. Sandri et al. 2012; Selva et al. 2014; Rutarindwa et al. 2019).

3 Types of Uncertainty: Aleatory Versus Epistemic

We tend to think of “uncertainty” either in terms of an error (like the measurement error) or to describe an inherent impossibility to predict the outcome of a given process. A common categorization of uncertainty types divides them into aleatory and epistemic uncertainties, and ontological error (e.g. Marzocchi and Jordan 2014).

Aleatory uncertainty is linked to the intrinsic unpredictability of the outcome of a process, and it is irreducible by the nature of the process: for example, in throwing a 6-sided die, the probability of getting any number between 1 and 6 is largely linked to the aleatory uncertainty. The epistemic uncertainty is linked to lack of knowledge about the process, and, conversely, it is, in principle, reducible by acquiring more information on the process. In the same example of the die, incomplete knowledge about the fairness of the die (for example, if we do not know that it has an imperfection causing an imbalance) represents a source of epistemic uncertainty. Any additional information regarding the type of imperfection could be reflected in the calculation of the probability of getting numbers between 1 and 6, and might reduce the epistemic uncertainty. Finally, the ontological error is related to what “we do not know (that) we do not know”. For example, if we did not know that the die we were about to throw was not a 6-sided but an 8-sided die, the entire characterization of aleatory and epistemic uncertainty would need to be adapted (Marzocchi and Jordan 2014). Therefore, it is important to stress that defining an unequivocal categorization of uncertainty types lies at the core of probabilistic hazard assessments (e.g. Marzocchi et al. 2021), for the way data are collected, processed and modeled influences the quantification of both aleatory and epistemic uncertainty (cf. Rougier 2013; Rougier and Beven 2013).

Another way to appropriately describe the differences between aleatory and epistemic uncertainty is through the Ellsberg paradox. Suppose you have two boxes (Fig. 1). In both boxes you have K balls: in the left box (BOX 1) you have 50% white and 50% black, in the right one (BOX 2) the proportion is unknown. What is the best box to blindly draw a ball if you want to blindly pick a black ball? In order to answer this question, we can define the probability density function describing the expected frequency,

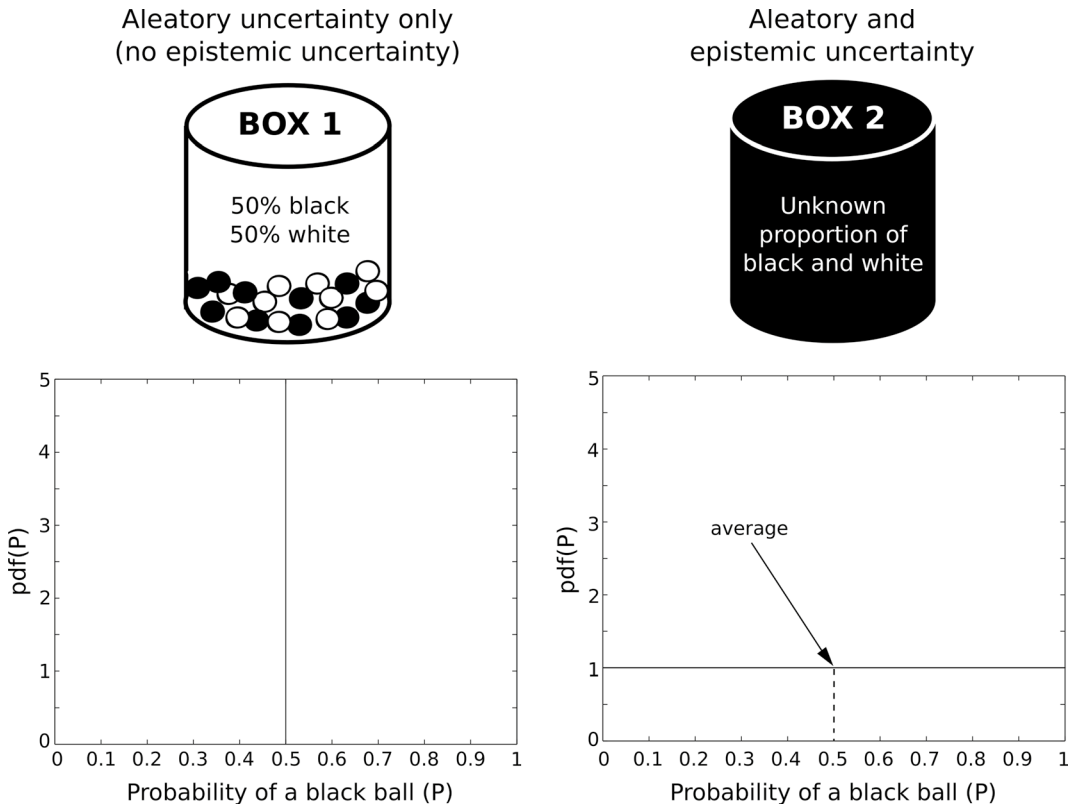


Fig. 1 The Ellsberg paradox. The top row shows the two boxes with different types of uncertainty. The bottom-row plots show the translation into probability density

functions for the probability to pick a black ball (adapted from Marzocchi et al. 2004)

P , to blindly pick a black ball. In BOX 1, it is exactly 50% and it can be described by a Dirac delta function centered on 0.5 (in unit probability, Fig. 1a), while in BOX 2 a uniform probability density function between 0 and 1 (Fig. 1b), describing each possible frequency value as equally probable, is best suited. Both these probability density functions have as best estimate (mean, or median) the value of 0.5. However, they do describe two end-member situations: in BOX 1, there is maximum aleatory uncertainty (as the estimate is equidistant from 0—i.e. picking a black ball is impossible and 1—i.e. picking a black ball is certain) but no epistemic uncertainty (as we know everything about the box, and the uncertainty is solely linked to the unpredictability of blind-picking a black ball); in BOX 2, both aleatory and epistemic

uncertainty are maximum, the latter related to the fact that we have no information on the true proportion of white to black balls. The paradox implicitly tells us two important stories: one is that describing a probability (or frequency) by its probability density function is much more complete and transparent, as it allows us to distinguish between situations characterized by different degrees and types of uncertainty. The other one is that the aleatory uncertainty can be described by a central parameter of the probability density function, such as the mean or the median, while the epistemic uncertainty can be quantified by the dispersion of the probability density function around this central value. And, going back to the paradox: what is then the best box to blindly pick a black ball from, if we were to win(/lose) a reward for each black(/white)

ball extracted? Well, in one-shot picking the probability is the same (50%), but in the long run, picking many times (and replacing the ball into the box each time), we will not win much from BOX 1, whereas we should be ready to win or lose a lot if we pick from BOX 2.

From the initial recognition of the importance of uncertainty as a fundamental part in forecasting and hazard assessment for natural events (e.g., Woo 1999; Aspinall et al. 2002), within a few years the volcanological community reacted and started proposing possible strategies to account for aleatory uncertainty in hazard assessment (e.g. Connor et al. 2001; Newhall and Hoblitt 2002) and for both aleatory and epistemic uncertainty in eruption forecasting (e.g., Aspinall et al. 2003; Marzocchi et al. 2004, 2008) and volcanic hazard assessment (e.g., Marzocchi et al. 2006, 2010; Neri et al. 2008; Sobradelo and Martí 2010).

Methodological approaches commonly used in volcanology to incorporate the quantification of uncertainty are Event Trees (e.g. Newhall and Hoblitt 2002; Marzocchi et al. 2008, 2010; Newhall and Pallister 2015; Wright et al. 2019), different methods of Expert Elicitation (e.g. Aspinall 2006; Cooke 1991; Selva et al. 2012a, b; Neri et al. 2015), Bayesian Belief Networks, BBNs (Aspinall et al. 2003; Tierz et al. 2017; Christophersen et al. 2018), Markov Chain Models (e.g. Aspinall 2006; Bebbington and Jenkins 2019), or Bayesian inversion of monitoring data into physics-based models (e.g., Anderson and Segall 2013; Anderson and Poland 2016; Gu et al. 2023). Increasingly often, one or more of these approaches are merged together, strengthening the advantages of each of them (e.g. parameterizing event trees or BBNs using expert elicitation, e.g. Aspinall et al. 2002; Selva et al. 2012a; Christophersen et al. 2018; or parameterizing BBNs using event trees, e.g. Tierz et al. 2017). These methodologies can be then implemented under a Bayesian interpretation of probabilistic hazard (e.g. Marzocchi et al. 2004, 2008, 2021) in which probabilities are not provided as single numbers but described by a probability density function (see above the Ellsberg paradox), allowing a full

quantification of the epistemic uncertainty associated with the hazard. Such *doubly-stochastic* approaches can be implemented using Bayesian Event Trees, BETs (Marzocchi et al. 2004, 2006, 2008, 2010); expert elicitation within BET (e.g. Selva et al. 2012a), but also using other statistical models which usually aim at dealing with specific aspects of the overall PVHA (e.g. Jaquet et al. 2006; Spiller et al. 2014; Bevilacqua et al. 2016).

4 Eruption Forecasting

A thorough review on the methods for long- and short-term eruption forecasting can be found in Marzocchi and Bebbington (2012). Here, we recap the basic methods and literature used in the two time frames, from basic concepts to suggestions for the reader.

4.1 Long-Term Analysis of Eruption Recurrence Times: Renewal Models

The time between the end of an eruption and the onset of the successive one is called “repose time”. Often, eruption occurrence in time is approximated as a point processes, i.e., neglecting the duration of the eruption itself which is, in general, much shorter than the time between successive eruptions: in such case, the “inter-event time” (IET), that is the time between two successive eruption onsets, is taken as the “repose time” or return period.

Since the sixties, repose times or inter-event times have been analyzed to infer some features of volcanic systems and mechanisms for magma feeding, and to forecast eruption occurrence in a given time interval into the future (e.g., Wickman 1966; Klein 1982; Mulargia et al. 1985). Following this approach, several probability distributions have been proposed to model repose times:

1. Simple exponential model for Poisson processes (e.g., De la Cruz-Reyna 1991;

- Marzocchi and Zaccarelli 2006), characterized by one parameter that is the mean return period, which also defines the mean rate of occurrence of eruptions;
2. Failure models based on the Weibull distribution (e.g., Voight 1989; Bebbington and Lai 1996), characterized by two parameters, where the probability of event occurrence may increase/decrease in time, depending on the value of the shape parameter;
 3. LogLogistic models (Connor et al. 2003), typical of point processes in which two competing factors are acting, one favoring and one inhibiting the occurrence of an event as the time from the last event increases;
 4. Power-law models, characterized by possible infinite variance and mean (Pyle 1998);
 5. Models characterized by self-exciting processes acting on the event rate (also called “intensity” in the literature), meaning that every event increases the likelihood of a subsequent event, but this influence decreases with time (Bebbington and Cronin 2011; Bevilacqua et al. 2016);
 6. Inverse Gaussian model, also termed Brownian Passage Time, which is characterized by a parameter linked to the mean repose time and an “aperiodicity” parameter, measuring the aperiodicity of the mean response of the system (Garcia-Aristizabal et al. 2012, 2013), and describing a system in which small perturbations are superimposed to a load-and-discharge process. This model becomes similar to the Exponential one for very long repose times, and has proved useful to compare different systems spanning from periodic-like to Poisson-like (aperiodic) systems;
 7. Lognormal models, usually describing a quasi-periodic behavior (Bebbington and Lai 1996);
 8. Mixtures of some of the above distributions, as e.g., mixture of exponentials (Mendoza-Rosas and la Cruz-Reyna 2008) or mixture of Weibulls (Turner et al. 2008), to describe multi-modal processes.

All these models assume that the repose times in a given catalog are a sample from a common parent distribution that governs a stationary process generating the data. With the term “stationary” we refer to the model parameters (meaning that they do not change over time) and not to the probability of an event in a given time interval (which may change in time depending on the model assumed).

However, a frequently observed feature in volcanic activity is its tendency to concentrate within ‘short’ temporal intervals, that is, to occur in clusters in the time domain, with different characteristics depending on the volcanic setting studied (e.g., Conway et al. 1998; Cronin et al. 2001; Bebbington 2010; Bevilacqua et al. 2016; Sandri et al. 2021; Selva et al. 2022).

4.2 Short-Term Eruption Forecasting: Observables and Models

One basic objective of short-term (e.g. days to weeks) volcanic hazard assessments is to identify increases in the probability of eruption, related to changes in measured observables, *before* the onset of an eruption. Once in progress, the median duration of eruptions is seven weeks so forecasting short-term changes in eruptive intensity and/or style, especially at volcanoes which may be persistently active and/or whose eruptions may be long-lasting is critical to identify changing hazard probabilities (e.g. Jenkins et al. 2007; Chouet and Matoza 2013; Ogburn et al. 2015; Wolpert et al. 2018; Bebbington and Jenkins 2019, 2022). Seeking to address needs of decision-makers, some studies have also looked at providing probabilistic estimates for the eruption duration and/or the end time of eruptions (e.g. Aspinall et al. 2002; Gunn et al. 2013; Wolpert et al. 2016; Bebbington et al. 2018; Spiller et al. 2020). Finally, frontier studies aim at anticipating eruption occurrence by several months, such as Galetto et al. (2022), who have found that, at mafic calderas,

the larger the magma intrusion rate inferred from surface deformation, the larger the probability of an eruption in months up to a year.

In terms of observables, surficial and sub-surface observations of magmatic and volcanic phenomena have been the main source of data used to inform short-term hazard assessments and the related physical and statistical models required to carry out the analysis. Pre-eruptive forecasts have historically relied upon three main pillars of volcano monitoring signals: seismicity, ground deformation and volcanic gas outputs (e.g. Scarpa and Tilling 2012; Newhall and Hoblitt 2002; Sparks 2003; Selva et al. 2012a, b; Hincks et al. 2014). Other strands of evidence which have been proposed as informative to assess changes in the short-term probability of eruption have been: sub-surface gravity (e.g. Carbone et al. 2017), muon tomography (e.g. Nomura et al. 2020) or aquifer hydrology (e.g. Strehlow et al. 2015).

The methodologies adopted to include observables/anomalies in short-term eruption forecasting and hazard assessment are:

- Expert elicitation techniques, in which the informed judgment of a panel of experts is distilled after exposing them to the set of observations or anomalies and the description of the ongoing volcanic unrest. Elicitation can be either “direct” (e.g., Aspinall 2006), if experts are elicited directly for the probability of some relevant events (e.g., the probability of magmatic unrest, of eruption, of phreatic explosion, of a given hazardous event impacting a specific site); or it can be “indirect” (e.g., Selva et al. 2012a), if experts are elicited to define what anomalies are deemed relevant to increase the probability of the relevant events. The former type is somewhat quicker, hence more suitable to be adopted during a volcanic crisis. Nonetheless, it has the shortcoming of expert volcanologists not necessarily being familiar with translating their expertise and experience into quantifying probabilities. A way to deal with this problem is to weight experts

according to their capability to provide accurate, and possibly precise, assessments of probability ranges of uncommon events: this capability is then measured by exposing experts to “seed questions” whose answer is unknown to them but known to the “elicitor”. Indirect elicitation is instead better suited to analyses carried out in “peacetime” (i.e. outside a crisis). Having specified a clear set of rules among elicitors and elicited experts, the team can focus on the definition of volcanic unrest at the given volcano(es), and on what it would be expected to observe and measure in case the unrest evolves into other relevant events (e.g., magmatic unrest, eruption, phreatic explosion). A shortcoming of this type of elicitation is that it needs to be coupled with a model that translates anomalies into probabilities, e.g., BET (Marzocchi et al. 2008) or BBN (Aspinall et al. 2003; Hincks et al. 2014) (see following points).

- Event Trees (e.g., Newhall and Hoblitt 2002; Wright et al. 2019) are probabilistic graphical representations of volcanic events (Fig. 2) starting from a general parent node (typically volcanic unrest), and branching towards subsequent nodes that describe more specific events, and are conditional to the previous event(s): that is, magmatic or hydrothermal unrest conditional to unrest; magmatic eruption conditional to magmatic unrest; and so on. Their graphical and conditional nature helps in branching the complex processes related to eruption forecasting and/or volcanic hazard assessment into logical and conditional steps, easier to understand, assess and communicate. For example, lists of possible anomalies linked to volcanic unrest can be associated with specific nodes, so changes in probability of events can be attached to specific patterns of anomalies, when/if detected. Among Event Trees, Bayesian Event Trees (BET_EF: Marzocchi et al. 2004, 2008; Lindsay et al. 2010; BET_stVH, Selva et al. 2014; BET_UNREST, Tonini et al. 2016) are models in which the detection of an anomaly is “fuzzy”, that is,

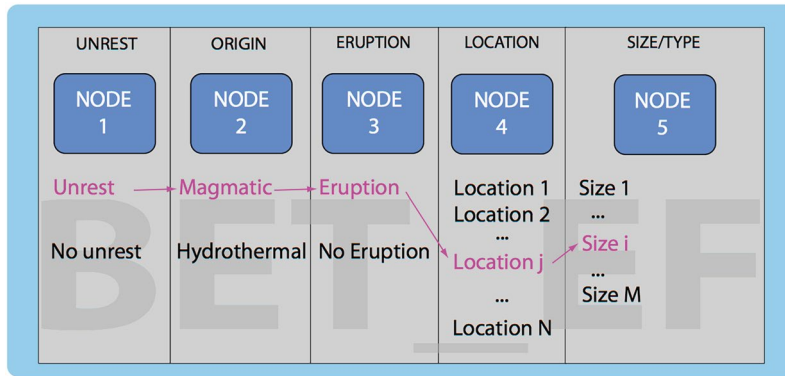


Fig. 2 An example of event tree: at subsequent nodes (blue boxes) the probability conditional to the previous node is calculated, by means of data from the geological record, models and/or monitoring observations (depending on the time scale, see Sect. 2). The probability in the final outcome of interest is then achieved by multiplication of the conditional probability of the outcome by all

the conditional probabilities along the path to reach that outcome, backward to the “Unrest” node. In the example, we can compute the probability of a magmatic eruption of size i (out of M possible sizes) and vent position j (out of N possible vent positions) by multiplying all the conditional probabilities along the pink path. Adapted after Marzocchi et al. (2008, 2010)

an observable (e.g. a monitoring parameter) does not necessarily overcome a sharp, single threshold to become anomalous. Instead, a ‘degree of anomaly’ between 0 and 1 is assigned to the observable, covering a range of its values over which the parameter is considered to be ‘partially anomalous’ (Fig. 3). Below a first threshold, the observable is not anomalous. Above a second threshold, the observable is ‘certainly anomalous’ (Fig. 3). In these models, the translation of an anomaly into a best-evaluation probability of, say, eruption occurrence, follows the idea that the first few detected anomalies are most informative, and further anomalies are less and less important in upgrading the best-evaluation probability (Fig. 3). Nevertheless, changes in this probability will also depend on the relative importance (or weight—assigned by the panel of experts) of the specific anomalous parameter in conditioning the probability of occurrence at a given node/event (e.g. Selva et al. 2012a).

- Bayesian Belief Networks, BBNs (e.g. Aspinall et al. 2003; Hincks et al. 2014; Cannavò et al. 2017) are directed and acyclic probabilistic graphical models providing a structure for the complex processes

governing volcanic activity and outcomes. The graph represents a set of random variables as “nodes” and the relationships between nodes as “arrows” or “arcs” pointing from a “parent” node to a “child” node, commonly expliciting causal relationships. Some nodes are related to “hidden” states that cannot be observed directly, but may be inferred on the basis of “observable” nodes linked to them, and which can be directly parameterized using real monitoring observations (Fig. 4). Along with the probabilistic graph, a set of tables specifying either a marginal probability distribution (for nodes without parents), or a conditional probability distribution (child node conditional on parent(s) node(s)) are required. BBNs enable inference on key volcanic states and processes, and their graphical nature makes them an efficient and intuitive means for describing complex processes, like volcanic processes leading to an eruption.

- Stochastic version of the Failure Forecast Method (FFM): FFM is a method originally developed to deterministically predict landslide occurrence on the basis of monitoring data interpreted as potential landslide precursors. The method solves the material failure law (representing the potential cascading

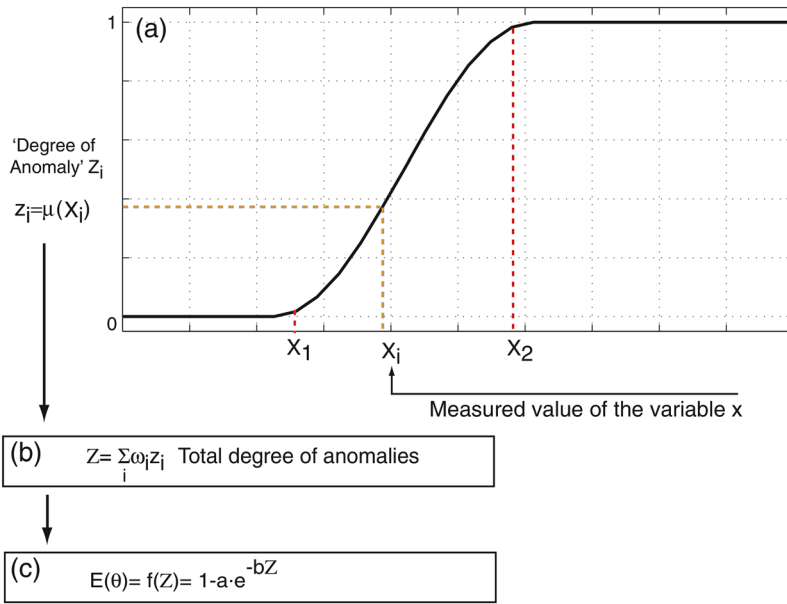


Fig. 3 This figure explains how monitoring measures can be transformed into a best-estimate probability at a given node of a Bayesian Event Tree (BET). A monitoring measure x_i is first translated into a degree of anomaly z_i according to a selected anomaly function $\mu(\cdot)$ (a). In the example given, a measure below x_1 is considered background, above x_2 is (fully) anomalous, and in between it has an intermediate ‘degree of anomaly’. After collecting the degree of anomaly for

all parameters considered at the node, they are combined using a weighted mean (ω_i is the weight of the i -th parameter) in order to obtain the total degree of anomaly (b). Then, the total degree of anomaly is transformed into a mean probability at the node using a predefined function. In BET models, the function used is shown in (c). At each node, the parameters, weights, and thresholds are selected by the user(s), possibly through expert elicitation. Modified from Marzocchi and Bebbington (2012)

of precursory events, e.g., growth and coalescence of small cracks leading to a large-scale rupture of the material) applied to monitoring data. In volcanology, it was first applied, in its deterministic meaning, retrospectively after the 1980 Mt St Helens eruption (Voight 1988), and it has been applied later on to seismic (e.g., Kilburn and Voight 1998; Kilburn 2003) and deformation data (e.g., Bevilacqua et al. 2020) at several volcanoes displaying unrest. Recently, it has been nested within a so-called “doubly-stochastic” method by Bevilacqua et al. (2019) by incorporating a stochastic noise term in the original material failure law, and thus including uncertainty in the estimation. The

doubly-stochastic formulation is particularly powerful, in the sense that it provides a complete posterior probability distribution, allowing users to determine a worst case scenario with a specified level of confidence. The main shortcoming of the method is that it has always been applied retrospectively, but never successfully for a future event. The main reason is that it may be very hard to detect accelerations in the monitoring data (e.g., in seismic counts, or in released seismic or deformation energy) in real time, whereas these accelerations usually appear much more clearly when monitoring time series are examined ex-post the occurrence of the eruption.

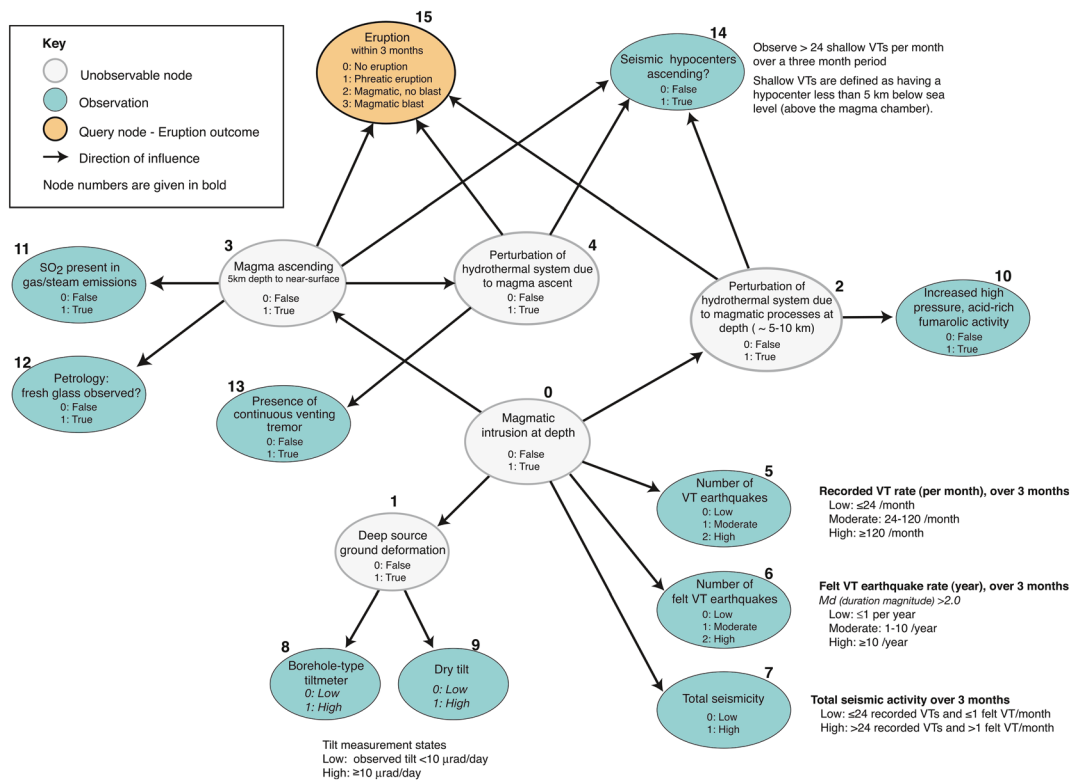


Fig. 4 Bayesian Belief Network diagram for La Soufrière de Guadeloupe, from Hincks et al. (2014), showing the relationship between volcanic processes, states and observations available during the unrest episode in 1976, and used to forecast future activity. Nodes represent both hidden (gray) and observable (blue) states. The arcs between nodes represent conditional dependencies (e.g. direct causal relationships or influence) and are quantified by conditional probability tables. The arrows indicate the

direction of influence e.g. venting tremor (Node 13) is believed to be a sign of perturbation of the hydrothermal system resulting from magma ascent (Node 4). The conditional probability distributions (and associated uncertainties) for the tables can be obtained by expert elicitation (as, for example, in the case of Hincks et al. 2014), or, in case of data-rich applications, they can be estimated purely from data, or a combination of observations and prior knowledge (e.g. Cannavò et al. 2017)

5 Probabilistic Volcanic Hazard Assessment (PVHA)

Complementary methods have progressively been exploited to assess volcanic hazard in the recent decades. Conventional studies, based on geological maps and field surveys, display the extent of the preserved products from past eruptions and represent a key basis for PVHA. However, such studies provide minimum estimates (although, depending on the phenomenon and place, they can be fairly robust), and they seldom consider phenomena (in type or size) that

have no trace in the geological record of the volcano studied. More detailed hazard studies are based on one or a few sets of *representative* eruption scenarios, in which the extent of the different eruptive products is given either for a specific expected size (e.g. Orsi et al. 2004) or separately for a series of likely scenarios (Hayes et al. 2020). In addition, some studies assess the relative probability and sometimes provide a typical recurrence time for each scenario (e.g. Thouret et al. 1999). More sophisticated hazard studies are based on semi-empirical and statistical modeling (e.g. Iverson et al. 1998; Favalli et al. 2009)

or physical modeling (e.g. Esposti Ongaro et al. 2008; Kelfoun et al. 2009) of specific hazardous phenomena, where numerical models play a pivotal role, for example to simulate the tephra dispersal and deposition or the propagation of pyroclastic density currents and/or lava flows.

Other authors have integrated the aforementioned approaches with detailed field observations (e.g. Bonadonna 2006; Cioni et al. 2008; Lirer et al. 2010). Finally, most recent hazard studies are based on a probabilistic approach that integrates the results of numerical models (e.g., Del Negro et al. 2013; Titos et al. 2022; Massaro et al. 2021; Jenkins et al. 2022), and that may include the elicitation of opinions from a team of experts (e.g. Neri et al. 2008, 2015) and/or the use of probabilistic event trees (e.g. Selva et al. 2010, 2014; Martí et al. 2008; Sandri et al. 2012, 2014, 2018; Biass and Bonadonna 2013; Strehlow et al. 2017; Martínez-Montesinos et al. 2022) or Bayesian Belief Networks (Tierz et al. 2017).

5.1 Sources of Uncertainty in PVHA

The common factor that must be accounted for in all PVHA is related to the intrinsic variability (i.e. aleatory uncertainty) in the possible eruption size and/or style. This is true for all volcanic hazardous phenomena, and conditions PVHA through the need of choosing values, ranges and probability density functions for the eruptive parameters related to the volcanic source: for example eruption magnitude (total erupted mass), eruption intensity (mass eruption rate), or eruption duration. The variability in the eruption size or style is commonly tackled by dividing the possible sizes or styles into a few eruptive classes, each represented by a specific (set of) eruptive scenario(s). Examples of this approach are numerous in literature (just to mention a few examples: Selva et al. 2010; Sandri et al. 2014; Bonadonna et al. 2005; Martí et al. 2008; Mead and Magill 2017).

The variability in the vent location is also relevant at volcanic fields (e.g., Auckland

Volcanic Field, Sandri et al. 2012) or large calderas (e.g., Campi Flegrei, Italy: Selva et al. 2012b; Bevilacqua et al. 2015; Rivalta et al. 2019; Long Valley, USA, Bevilacqua et al. 2017a, b; Okataina, New Zealand: Thompson et al. 2015) or large volcanic edifices characterized by spatially variable centers of activity over time (e.g., Mt Etna, Cappello et al. 2012), and, for long-term purposes, it is generally evaluated by accounting for the position of indicators of magma preferred pathways, such as past eruptive centers or fissures. We point the reader to Le Corvec et al. (2013) and Connor et al. (2018) for reviews on the topic of analyzing and modeling vent-opening locations at volcanic systems. In terms of innovative approaches, Rivalta et al. (2019) propose a forward-modeling approach to the problem, by simulating the trajectories, and intersections with the surface (proxy for vent location), of magmatic dikes at Campi Flegrei (Italy). Their modeling is informed by the stress field acting on the caldera, to identify where the most likely stress-favorable areas for magma rising are.

Depending on the hazardous event considered, there are other factors that may affect its propagation and impact, in some cases with overwhelming importance.

For tephra dispersal and fallout, and gas dispersal, the wind field is obviously a dominant source of uncertainty on PVHA, and it is usually accounted for by running thousands of different simulations with variable wind fields sampled from a representative time period (just as examples for tephra fallout: Costa et al. 2009; Biass and Bonadonna 2013; and for gas dispersal: Granieri et al. 2015). For volcanic mass flows, such as lava flows, PDCs or lahars, the resolution of the digital terrain model (DTM) is an important factor in the analysis (e.g. Stefanescu et al. 2012; Chevrel et al. 2021), although the overall relevance of this can be both volcano- and model-specific. For example, Tierz et al. (2016) developed a comprehensive quantification of the impact of different sources of epistemic uncertainty on PDC hazard modeled through the energy cone (Malin and Sheridan 1982) and found that uncertainty on the DTM

was less important than other sources, highlighting the value of analyses aimed at ranking different sources of (epistemic) uncertainty. Consideration of changing topography over even short time periods should ideally be taken into account, although it is still remarkably challenging to incorporate this aspect into PVHA. For example, the progressive collapse of a lava dome over minutes/hours/days can rapidly fill topography with deposits leading to more widespread and devastating impacts from subsequent flows (e.g. Loughlin et al. 2002).

5.2 Long-Term PVHA: Statistical Combinations of Ensembles of Eruptive Scenarios

As mentioned above, in order to achieve quantitative PVHA for long-term purposes, scientists usually define a set of representative eruptive scenarios, and ascribe a set of Eruption Source Parameters (ESP) which are plausible for those scenarios. The ESPs are then used as input in numerical model(s) (or simulator(s)) of the hazardous phenomenon studied to achieve an ensemble of simulations that can be aggregated to calculate, at each grid point, the frequency of simulations reaching or exceeding a specific threshold in hazard intensity (see Sect. 5.4). This frequency can be interpreted as the hazard conditional to the scenario occurrence. There are several examples of this application: just to provide the reader some hints, we refer to Bonadonna et al. (2005) and Costa et al. (2009) for tephra-fallout examples; Favalli et al. (2009) and Del Negro et al. (2013) for lava flows; Biass et al. (2016) and Massaro et al. (2021) for ballistics.

Less frequently, the hazard evaluations conditional to different scenarios are weight-combined, with weights corresponding to the probability of each scenario: the result is the hazard conditional to the eruption occurrence, as presented, for example, in Neri et al. (2015), Clarke et al. (2020) for PDCs; Selva et al. (2010), Titos et al. (2022) for tephra fallout; Mead and Magill (2017) for

lahars, or Gjerløw et al. (2022) for different types of hazardous events.

Finally, if long-term forecasts of eruption occurrence are available, and/or if the probability of different scenarios has been calculated, an absolute long-term hazard assessment can be achieved, by accounting also for the eruption forecast. Examples of these assessments, which can then be used for quantitative risk assessment and ranking, can be found in Thompson et al. (2015), Strehlow et al. (2017) and Sandri et al. (2014, 2018) for different hazardous events.

Given the ever-increasing computational capability, the run of thousands to tens of thousands of simulator instances is becoming more and more feasible and cheap: this allows users to define a probability density function for each ESP, then randomly sample such distributions (using Monte Carlo or Latin Hypercube Sampling methods, for example), then run one simulation for each realization, combined with samples of key initial conditions such as wind direction and speed for tephra or gas dispersal. In turn, this means exploring the uncertainty at an unprecedented level of detail, also in terms of spatial scale (we can now afford target domains of thousands of km at a few-km resolution, see Titos et al. 2022; Martínez-Montesinos et al. 2022), and in terms of possible volcanic sources to account for (see Jenkins et al. 2022 for a systematical analysis of Southeast Asia volcanoes and different hazardous phenomena). Notwithstanding, it is also important to note that complex simulators tend to imply long to very-long runtimes per each simulation (e.g. Esposti Ongaro et al. 2008). Therefore, the Monte Carlo integration of many thousands of model outputs described above does not always represent a feasible strategy to quantify uncertainty. Consequently, other uncertainty quantification techniques are also being increasingly sought and used in the volcanological community. A few examples of this are found in Dalbey et al. (2008), Madankan et al. (2014), Tierz et al. (2018), for polynomial-expansion methods; and Bayarri et al. (2009), Spiller et al. (2014), Rutarindwa et al. (2019) for stochastic-process emulators.

5.3 Short-Term PVHA: Combining Eruptive Scenarios with Data from Volcano Monitoring

While long-term hazard assessment mostly relies on the exploration of the uncertainty in the size and location of eruptions and eruptive phenomena, as well as the uncertainty in other ‘external factors’ (e.g., the wind), short-term PVHA can benefit from the monitoring data ingested in an operational environment both to continuously update the eruption forecast (see Sect. 4.2) and to narrow down the vent position uncertainty (for example, the location of seismic epicenters or of deformation sources can be informative of where the vent may open). An example of this short-term evaluation is given in Sandri et al. (2012) during the Ruamoko exercise held in Auckland, New Zealand, in 2010, where the probability of eruption and the spatial probability of vent opening were updated during the exercise as new monitoring evidence was gathered. When coupled with simulations of events that are strongly influenced by topography, for example PDCs, the information on the spatial probability of vent opening can be crucial to effectively assess the associated volcanic hazard (e.g. Bevilacqua et al. 2017a, b; Sandri et al. 2018; Rutarindwa et al. 2019). A similar approach can be taken for actively growing lava domes, where ground-based or remote observational data can enable assessment of the volume of unstable material available for collapse, its location and hence enable modeling of potential PDCs (Wadge et al. 2008; Pallister et al. 2019b).

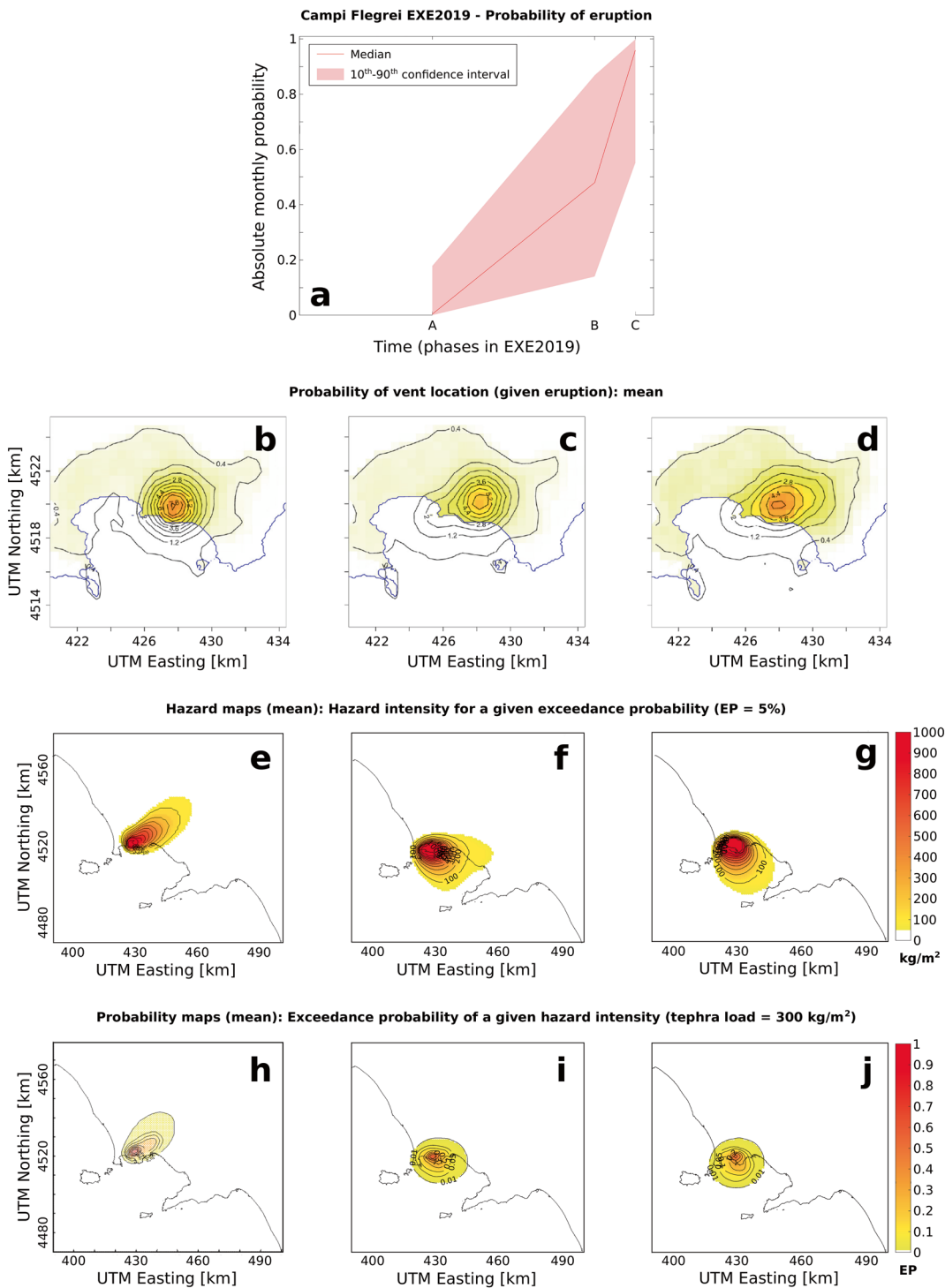
Short-term hazard assessment for tephra fall and gas dispersal can benefit from updated weather forecast (e.g., Volcanic Ash Advisory Centers) so that a specific set of dispersal

simulations can be launched when the new forecast is available, focusing only on the uncertainty on the eruption size and related ESPs, and vent location inferred from the position of monitoring anomalies, as shown for example in Selva et al. (2014, 2015) and Martínez-Montesinos et al. (2022). An example is given in Fig. 5 where the results achieved during the 2019 exercise at Campi Flegrei are shown. In particular, the probability of eruption changes in time (Fig. 5a) due to the anomalies observed in seismicity, ground deformation and gas emissions; the spatial probability map of the vent position also changes in time (Fig. 5b–d) according to the spatial location of such anomalies; and the PVHA for tephra fallout changes in time (Fig. 5e–j) due to the overall changes in the eruption probability, vent-opening map and forecasted wind.

While a precursor of the eruption size among the monitoring data has not yet been identified, this is a frontier subject of research, where the possibility to identify precursors in the future (e.g., Wright et al. 2019) is also debated: for example, Papale (2018) defended eruption size as a scale-invariant variable, hence casting doubts regarding the possibility of forecasting eruption size based on the assumption that small and large eruptions are linked to different fundamental processes. In any case, future studies will need to address the quantification of the probability of eruption size of impending eruptions, primarily focusing on their potential explosivity. At present, this is commonly done on event trees based on the past frequencies observed at the volcano under study and/or at its analogues (e.g. Newhall and Pallister 2015), with no input from the monitoring. However, this could be improved if more (open) data became available

Fig. 5 Overview of short-term PVHA results. Panel **a** shows the time evolution of the probability of eruption (solid line: median probability; shaded area: 80% confidence interval) in the following month, as it evolved during the 3 phases of the ExeFlegrei exercise (A, B, C on the x-axis) held at Campi Flegrei, Italy, in October 2019. Panels **b** to **d** show the evolution of the vent opening probability map conditional to an eruption, from

phase A (panel **b**) to phase C (panel **e**). Panels **e** to **g** show the evolution of the hazard map for tephra ground accumulation at 5% probability, conditional to an eruption, from phase A (panel **e**) to phase C (panel **g**). Panels **h** to **j** show the evolution of the probability map for tephra ground accumulation exceeding 300 kg/m², conditional to an eruption, from phase A (panel **h**) to phase C (panel **j**)



(e.g. Newhall et al. 2017; Tierz 2020) as well as by using enhanced conceptual and/or computational models (e.g. Poland and Anderson 2020). Nevertheless, it should also be recognized that, just as with earthquakes, eruptions may start small and (rapidly) escalate, hence posing an additional, inevitable question of how far escalation can progress (e.g. Aspinall and Woo 2019). Recent research on the use of Markov-Chain models, coupled with sets of analogue volcanoes, represents an encouraging approach to address, in probabilistic terms, such ‘intra-eruption-forecasting’ challenges (Bebbington and Jenkins 2019, 2022).

5.4 Modern Representation of PVHA

As mentioned in the introduction, PVHA is one of the basic ingredients of quantitative volcanic risk analysis. In particular, key questions in PVHA, which, coupled with vulnerability and exposure analyses, can prove invaluable for volcanic risk assessments, are the following:

- What is the (exceedance) probability of a given hazardous volcanic event impacting a given point in space, within a specific time window, with a hazard intensity (e.g. dynamic pressure) above a given threshold?
- Complementarily, what is the expected hazard intensity associated with a given hazardous volcanic event impacting a given point in space, within a specific time window, with an exceedance probability above a given threshold?

Answers to these questions are coded within a fundamental hazard product derived from PVHA: the hazard curve (Fig. 6, e.g. Connor et al. 2001; Tonini et al. 2015; Tierz et al. 2018). A hazard curve, which represents a key element in probabilistic hazard and risk assessments outside volcanology (e.g. Bazzurro and Cornell 1999; Rougier et al. 2013; Horspool et al. 2014), displays values of hazard intensity on the x -axis and their associated values of exceedance

probability (i.e., the probability to exceed each of the thresholds) on the y -axis for a given spatial point in the target domain (for example, an airport, a school, a hospital, or a generic grid point). By definition, a hazard curve is a monotonically decreasing function, as the probability to exceed increasing thresholds decreases monotonically. In practice, a hazard curve is complementary to the cumulative distribution function for the hazard intensity, and hence equivalent to the ‘survivor function’ (e.g. Rougier 2013). If hazard curves are available at grid points covering a large-enough spatial hazard domain, one can customarily draw *probability maps* and *hazard maps* (e.g. Tonini et al. 2015) to answer the above questions. This is accomplished by ‘slicing’ the hazard curve at each grid point either vertically or horizontally, at specific thresholds of hazard intensity or exceedance probability, respectively (Fig. 6).

Thus, a probability map (usually, a contour or shaded map in probability units, see e.g. Figure 6, right-hand-side panels) shows, at each point of a grid covering the hazard domain, the probability to experience the hazardous event above a selected threshold in hazard intensity, within the considered time window (for example, for tephra fallout, 300 kg/m² in 50 years). Conversely, a hazard map (again, a contour or shaded map but in hazard-intensity units, see e.g. Fig. 6, bottom-row panels) shows, at each point of the grid, the hazard-intensity value that has an exceedance probability equal to a selected threshold, within the considered time window (for example, an exceedance probability of 0.01% in 1 year). Examples of hazard-intensity measures (e.g. Murnane et al. 2019) in PVHA are:

- tephra load units (such as kPa or kg/m²) for tephra fallout hazard critical for ground mobility (here, 1 kg/m² is a critical threshold) or roof collapse (here, 100–300 kg/m² are critical thresholds);
- tephra concentration units (such as g/m³) for airborne tephra hazard critical for aviation;
- flow thickness units (in m), speed units (m/s) and dynamic pressure units (kPa) for the

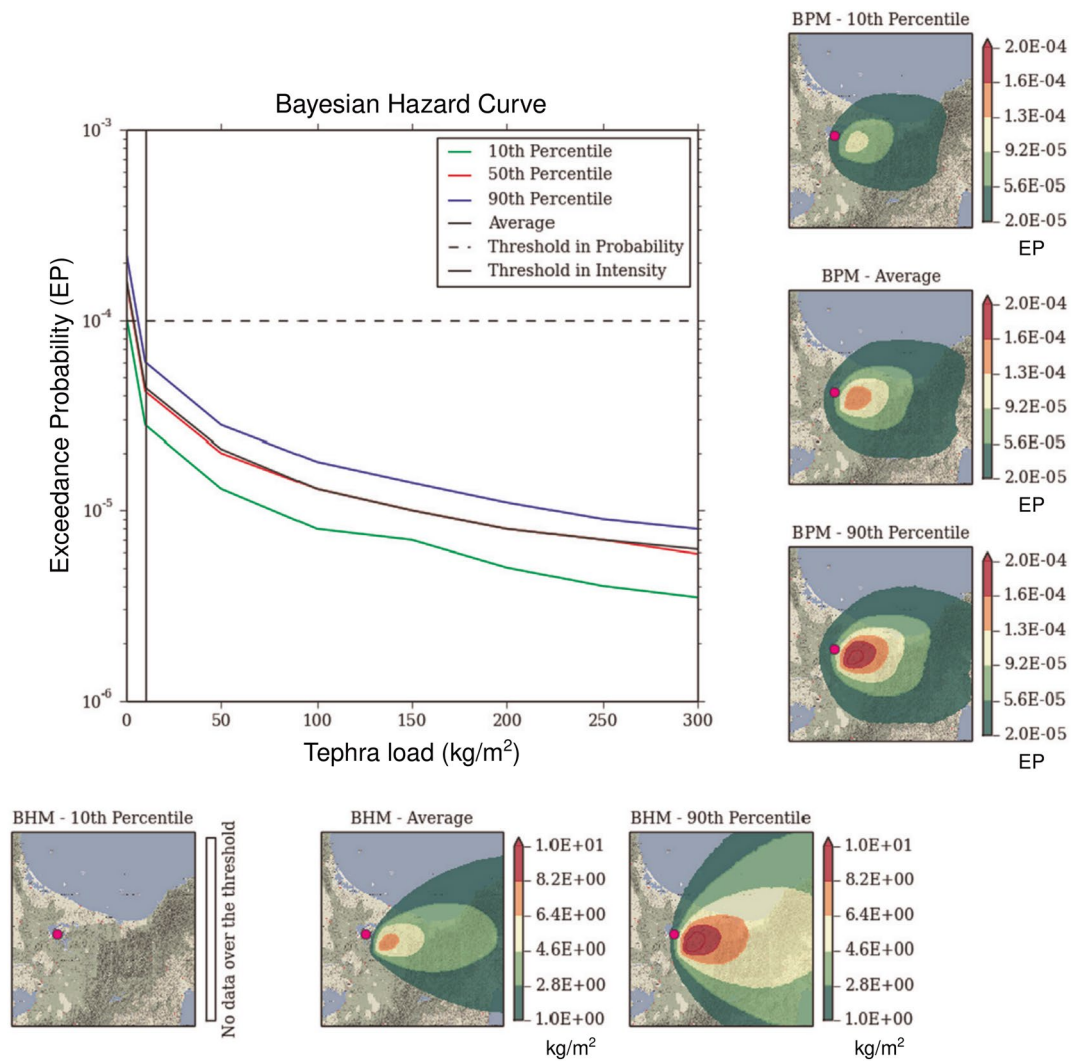


Fig. 6 Overview of PVHA results. The main picture is the Bayesian hazard curve for the point represented by the magenta dot in all small maps (illustrative example: the airport of Rotorua in New Zealand), showing on the y-axis the mean (solid black line) and the 10th (solid green), 50th (solid red) and 90th (solid blue) percentiles as a function of tephra loading (kg/m^2) on the x-axis. The corresponding best-evaluation (average) probability/hazard maps are shown respectively for a tephra load of 10 kg/m^2 (middle panel in right column) and for a probability of 10^{-4} per year (middle panel in bottom row). Similarly, the maps relative to the 80% confidence interval are shown, i.e. the same maps but cutting the 10th

and 90th percentile hazard curves (top and bottom panels in right column for probability maps; left and right panels in bottom row for hazard maps): the percentiles' probability maps have been obtained by intersecting the hazard intensity threshold (vertical solid black line) with the percentiles' hazard curve in each point of the target domain, at the selected tephra load threshold of 10 kg/m^2 . Similarly, the percentiles' hazard maps are obtained from the intersection between percentiles' hazard curves and the probability threshold (horizontal black dashed line) at the selected exceedance probability of 10^{-4} per year. Adapted from Tonini et al. (2015)

impact associated with mass-flows, such as PDCs and lahars.

If multiple models are used for PVHA and/or if a Bayesian approach is adopted (see Sect. 3), PVHA can be expressed by a set of hazard curves for a target point, expressing the epistemic uncertainty around the best-evaluation hazard curve (see Fig. 6). These additional hazard curves enrich the hazard description, as they provide the means to produce, not only a best-evaluation map (mean or median, describing the aleatory uncertainty) but also maps associated with other percentiles, which describe the epistemic uncertainty. For example, in Fig. 6 the 80% confidence interval is provided by further probability and hazard maps, by cutting the 10th and 90th percentiles' hazard curves.

5.5 A Few Words on Multi-hazard

Until recently, quantitative hazard assessment has often focused on a single type of hazardous phenomenon (e.g. Cioni et al. 2003; Sandri et al. 2012) for a number of reasons including data availability, computing power, time constraints, etc. Nevertheless, volcanic eruptions typically display a range of hazardous events (e.g. ballistic ejecta, tephra fallout, gas emissions, lava flows, PDCs, including 'classical' pyroclastic flows and surges, etc.) that may interact or occur concurrently and pose serious risk to human lives and assets. Commonly, the hazardous phenomenon considered by modelers is the one threatening the largest number of people or potentially causing the most widespread impacts, as in the case of tephra fallout. However, the focus on a single (although apparently major) hazardous phenomenon has important drawbacks: firstly, a single-hazard assessment, although useful, is not a complete assessment of volcanic hazardous phenomena that may occur during an eruptive event. Hazard assessments must be fit for purpose with clear caveats and limitations described: risk and emergency managers need robust evidence to support their decision making. For example, mitigating

the risk posed by other hazardous processes, potentially perceived as minor but less costly to mitigate, may be more rational according to some proposed volcanic risk metrics (e.g. Marzocchi and Woo 2009). Secondly, only proper homogenous assessments for multiple hazardous phenomena (e.g. Magill and Blong 2005a, b; Mosquera-Machado and Dilley 2009; Jenkins et al. 2022) can quantitatively rank them and identify those posing the highest risk. This is particularly significant for volcanoes, which are intrinsically multi-hazard systems, something that should always be kept in mind in the context of volcanic hazard and risk assessments.

Lastly, the hazard associated with one hazardous phenomenon can be profoundly affected by the previous and/or subsequent occurrence of other hazardous phenomena, either increasing or decreasing such hazard, and/or the vulnerability to it. Frontiers topics in PVHA are thus related to hazard interactions, mostly in two perspectives:

- at the hazard level (*cascading events*), implying that under some hazardous circumstances the probability of another hazardous event (and thus, its hazard) may increase, and this should be accounted for in proper multi-hazard and multi-risk assessments. The classical example is that during volcanic unrest the seismic hazard increases; another plausible example is the hazard from wildfires (Quah et al. 2022) during the phases of tephra fallout or ballistic ejection in proximal areas (an example is the Stromboli paroxysms occurred in the summer of 2019, when the ignition of tens of wildfires was observed as a result of hot ballistics falling over dry vegetation, Métrich et al. 2021). The interaction between hazardous phenomena is particularly important for lahars, which are intimately linked with the availability of loose pyroclastic material, commonly left by tephra fallout and PDCs on valleys and steep slopes of volcanoes (e.g. Pierson and Major 2014; Vallance and Iverson 2015). Therefore, quantitative hazard assessments that explicitly account for this volcanic-hazard interaction (e.g.

Volentik et al. 2009; Tierz et al. 2017) are a more complete version of PVHA compared to analyses that consider different hazardous phenomena separately (e.g. Sandri et al. 2014; Bevilacqua et al. 2021),

- at the vulnerability level (*concomitant events*), implying that the simultaneous occurrence of more than one hazardous event may enhance vulnerability. Here, the classical example is the occurrence of syn-eruptive seismicity in an area already blanketed by tephra fallout: the vulnerability of buildings to ground shaking is higher when their roofs are loaded with a layer of ash (Zuccaro et al. 2008). Likewise, the prolonged duration of volcanic unrest and eruption, with their associated multiple hazardous processes, can lead to complex socio-economic consequences (extensive risk).

6 Spatial Scales in Volcanic Hazard Assessment

6.1 Single-Volcano Hazard Assessments

Volcanic hazard assessments centered around a given volcanic system are by far the most common type of hazard assessment, probabilistic or not. Descriptive, qualitative or pseudo-quantitative, hazard assessments and products (e.g. maps) are used as base hazard knowledge for many volcanoes nowadays (e.g. Calder et al. 2015): in Chile (<https://rmvv.sernageomin.cl/peligros-volcanicos/>), New Zealand (<https://www.gns.cri.nz/our-science/natural-hazards-and-risks/volcanoes/volcanic-hazards/>) or Indonesia (<https://magma.esdm.go.id/v1/gunung-api/peta-kawasan-rawan-bencana>). On the other hand, probabilistic hazard assessments have also been developed over the last decades and have constantly grown in number and scope during recent times. Some reasons why probabilistic assessments are being increasingly sought at individual volcanoes (e.g. Marzocchi and Woo 2009; Marzocchi and Bebbington 2012; Rougier et al.

2013; Newhall and Pallister 2015; Calder et al. 2015; Pallister et al. 2019a; Tierz 2020; Poland and Anderson 2020) are the following: (i) they are able to capture, quantitatively, the substantial uncertainty that affects the volcanic hazard assessment; (ii) they aim at expanding on ‘experienced events’, hence depicting a more comprehensive picture of the overall volcanic hazard (and the multiple potential impacts); (iii) they are versatile products in terms of supporting decision making, e.g. land-use planning, cost-benefit analyses, etc.; (iv) they can be simplified into scenario-based assessments, at selected thresholds in the probability of occurrence (or hazard intensity) of each scenario (see Sect. 5.4).

A general approach to carry out single-volcano PVHA tends to involve the following elements (e.g. Pallister et al. 2019a): (1) geological and historical information on past eruptive behavior, events and products; (2) physical and statistical models to simulate eruptions and events both similar but also different from what is known about the volcano; and (3) data from volcanoes, eruptions and/or unrest episodes that are similar enough (*analogues*) as to justify its use to inform potential behavior and evolution at the volcano under study (e.g. Newhall et al. 2017). Going through this ‘chain’ of work can have huge costs in terms of fieldwork, geophysical and geochemical analyses, computational resources, etc., but, as noted before, PVHA is becoming more customary over time and can be supported, among others, through the sharing of resources amongst institutions as well as by the building and maintenance of large, open-access databases of volcanological data (e.g. Pallister et al. 2019a; Tierz 2020).

Example applications of probabilistic methods to compute single-volcano PVHA are now relatively common worldwide. Here, we highlight some of them, geographically:

- **South America:** large stratovolcanoes located close to densely-populated cities and critical infrastructure have been one focus of PVHA in the region. Two key hazardous phenomena analyzed have been PDCs and tephra fallout. For example: El Misti, Peru (Sandri

- et al. 2014; Charbonnier et al. 2020); and Cotopaxi and Guagua Pichincha, Ecuador (Tadini et al. 2022).
- **Central America and the Caribbean:** another example of two big metropolises (San Salvador, El Salvador; and Managua, Nicaragua) threatened by volcanic complexes dominated, respectively, by a stratovolcano (San Salvador volcano) and a volcanic field (Nejapa-Chiltepe) was provided by Bevilacqua et al. (2021). Specific challenges that long-lasting eruptions pose to PVHA, including forecasting the ‘end of the eruption’, were exemplified at Soufrière Hills volcano, Montserrat (Bayarri et al. 2009; Spiller et al. 2020).
 - **North America:** one theme that PVHA has addressed in the continent is the estimation of low-probability, high-consequence events, in particular concerning the long-term safety of nuclear facilities at large volcanic systems, for instance, in the Yucca Mountain region (Connor and Hill 1995) or the Snake River Plain volcanic area (Gallant et al. 2018). Other hazard assessments have stressed the importance of long-term PVHA for different volcanic hazardous phenomena at under-monitored volcanoes, like Ceboruco, Mexico (Constantinescu et al. 2022).
 - **Asia:** exposure of nuclear facilities to volcanic hazard has also been analyzed, for example, mainly from Mount Natib volcano (but also from Mount Pinatubo and Mariveles volcanoes, in a multi-volcano PVHA for tephra fallout), Philippines (Volentik et al. 2009). Tephra-fallout impacts on other types of infrastructure, caused by larger-than-usual explosions at frequently-active volcanoes, were explored at Sakurajima volcano, Japan, by Biass et al. (2017).
 - **Oceania:** the key influence of eruptive style (including the possibility of multi-phase eruptions) and vent location on PVHA has been analyzed, for example, at the Okataina Volcanic Centre, New Zealand (Bonadonna et al. 2005; Thompson et al. 2015). Other probabilistic hazard assessments have focused on rapid construction of probabilistic event trees for under-monitored, data-scarce volcanoes which may show signs of heightened unrest after centuries without any known eruption, e.g. Garbuna, Papua New Guinea (Newhall and Pallister 2015).
 - **Africa:** the use of probabilistic tools to rapidly assess lava-flow hazard at Nyamulagira volcano, DRC, was analyzed by Syavulisembo et al. (2015). At Aluto volcano, Ethiopia, a PVHA for PDCs, from data collection on the field to statistical modeling to quantify uncertainty, was carried out by Clarke et al. (2020).
 - **Europe:** several examples of PVHA have been developed for Napoli, in southern Italy, a city built on and/or surrounded by three volcanic systems (Somma-Vesuvius, Campi Flegrei and Ischia), and arguably the city with the highest volcanic risk in the entire continent (Selva et al. 2010; Neri et al. 2015; Sandri et al. 2016; Tierz et al. 2016, 2018; Bevilacqua et al. 2017b; Massaro et al. 2023). The Canary Islands, Spain, represent another high-volcanic-risk region, not only for its inhabitants but also because of the crucial role of tourism. Different approaches to PVHA have been presented for the volcanic systems of Teide, Tenerife (Martí et al. 2008; Martí and Felpeto 2010); El Hierro (Becerril et al. 2014), or La Palma (Martí et al. 2022).

6.2 Multi-volcano Hazard Assessments

Albeit considerably less common than single-volcano assessments, (probabilistic) volcanic hazard analyses that include multiple volcanoes into the calculation of volcanic hazard at a given point or area in space have also been developed, particularly in recent times. The presence, at scales ranging from local to national or regional, of a higher spatial density of volcanic systems and/or of a higher density of population (signaling a higher risk), tends to be associated with the need for multi-volcano hazard assessments (e.g.

Jenkins et al. 2012, 2018; Whelley et al. 2015; Sandri et al. 2016). For example, modeling by Jenkins et al. (2012) suggested that at least 55 volcanoes are capable of depositing ash in central Tokyo. The ingredients required in this type of assessment are basically equivalent to those defined above for single-volcano hazard assessments, with the additional complication that, potentially, every single volcano included in the multi-volcano PVHA should have, at least, its own description of aleatory uncertainty for the different components of the hazard assessment (e.g. Table 1 in Sandri et al. 2018). Reasonably, not always there will be enough data available for detailed quantifications of aleatory uncertainty for each and every volcanic system included in the PVHA. This is particularly true when tens of volcanoes are included in the analysis (e.g. Jenkins et al. 2012, 2022; Whelley et al. 2015). In any such situation, potential solutions usually involve one or two of the following approaches: (1) simplifying the description of aleatory uncertainty by using shared parameterizations within ‘groups of volcanoes’; and (2) defining such groupings based on, and/or using complementary data from, sets of analogue volcanoes (e.g. Sheldrake 2014; Whelley et al. 2015). The definition and application of such sets is becoming an ever-increasingly key component of single- and multi-volcano, short- or long-term, volcanic hazard assessments (e.g. Marzocchi et al. 2004; Mastin et al. 2009; Sandri et al. 2012; Ogburn et al. 2015; Newhall et al. 2017; Tierz et al. 2019, 2020; Bebbington and Jenkins 2022; Wang et al. 2022; Hayes et al. 2022), especially due to the pervasive lack of data available for many Holocene volcanoes (Loughlin et al. 2015), together with the realization that volcanological databases combined with sets of analogue volcanoes can be of great help in trying to fill in those data gaps (e.g. Ogburn et al. 2016; Newhall et al. 2017; Pallister et al. 2019a; Tierz 2020).

Examples of multi-volcano PVHA have tended to be strongly dominated by tephra-fall-out hazard analyses (e.g. Volentik et al. 2009; Jenkins et al. 2012, 2015b, 2018; Biass et al.

2014; Volentik and Houghton 2015). From a practical perspective, this is largely due to the fact that: (1) tephra is the volcanic hazard most likely to be experienced from multiple volcanoes because of its wider dispersal, compared to other volcanic hazardous phenomena, (2) datasets of regional wind fields required for such analyses are now openly available (e.g. Hersbach et al. 2020); and (3) local topography does not play a major role in tephra transport, thus reducing the complexity in the hazard modeling that topography imposes on PVHA for other hazardous phenomena such as lava flows, PDCs and lahars. When these phenomena have been considered in multi-volcano, multi-hazard PVHA, different degrees of simplification have been adopted: from defining hazard footprints based on a combination of terrain analysis (drainage basins) within radial buffers applied to the vent to assuming purely-radial hazard footprints around the volcanic vent (e.g. Aspinall et al. 2011), to simplifying eruptive scenarios with reduced natural variability, explored through small sample sizes, conditioned by the large number of volcanoes (40) analyzed (Jenkins et al. 2022). In the case of PDCs, to our knowledge, the only multi-volcano, comprehensive PVHA (i.e. including quantifications of both aleatory and epistemic uncertainty) published in the literature is Sandri et al. (2018), who analyzed PDC hazard in the metropolitan area of Napoli (Italy) from Somma-Vesuvius and Campi Flegrei volcanoes. The effect of considering both volcanic sources in the PVHA for PDCs was that of increasing the probability of PDC arrival (from at least one of the sources) at downtown Napoli, located between the two volcanoes. In areas closer to one of the two volcanoes, the corresponding source dominated that probability. Nevertheless, it was shown that the impact of the epistemic uncertainty in the whole PVHA for PDCs was complex, and could still be analyzed in more detail. For example, results in Sandri et al. (2018), together with previous research carried out at the volcanic systems (e.g. Orsi et al. 2004; Gurioli et al. 2010), suggested that different components are critical for PVHA of PDCs at the two

volcanoes: eruption size at Somma-Vesuvius and vent location at Campi Flegrei (cf. Tierz 2020).

6.3 National to Global Assessments

Probabilistic volcanic hazard assessments at national, regional and global scales are increasingly available in response to national and international policy frameworks that identify the need to better understand and reduce natural hazard risk at local to global scales (e.g. UNISDR 2015; UNDRR Global Assessment Report 2017, 2019; Ward et al. 2020). Volcanic hazardous phenomena and their impacts are not constrained by national borders so a trans-boundary, multi-scale approach to risk management is needed. Collaboration and cooperation between nations, institutions, public and private sector, civil society and NGOs is necessary to share data, information, planning scenarios, and to harmonize formats and approaches. This is being facilitated by increasing numbers of projects and initiatives (e.g. Murnane et al. 2019; Poljansek et al. 2021).

For the UNISDR 2015 Global Assessment Report, Jenkins et al. (2015b) produced the first global probabilistic ash fall hazard assessment building on methodologies developed at a regional scale for Southeast Asia (Jenkins et al. 2012). Volcanic ash fall is the most frequent and widespread volcanic hazard and is produced by all explosive volcanic eruptions. Although ash falls rarely endanger human life, they are frequent, occur during all explosive eruptions, cause direct and cascading impacts, and can be disruptive over a wide area, with long-lasting consequences. More recently, approaches to consider suites of related and potentially interacting hazardous processes have been developed at a regional scale (Jenkins et al. 2022) which can be combined with exposure to identify ‘threat’ and have potential to be developed to analyze impacts and/or losses.

Models at global or regional scales are typically only appropriate for long-term (years to decades) hazard estimation because of

high-level data requirements and analyses that typically prohibit near real-time assessment (Jenkins et al. 2015b). Comparative global studies that use harmonized approaches enabling ranking (of volcanoes) and/or the identification of high risk areas can enable the efficient allocation of national and international resources to reduce and manage risk. Risk reduction measures can be taken in the absence of full risk assessments but the more robust the evidence is, the more confident investors (e.g. NGOs) may be in positive outcomes.

Hazard and risk assessments at any scale need to be fit for purpose and ideally developed with potential users who may include civil protection and risk managers as well as at-risk populations. In order for probabilistic outputs to be used effectively, scientists may need to engage with users to explore their understanding of PVHA and their needs from design stage to completion. Volcano scientists will ideally understand real-world problems through interaction with transdisciplinary teams and ensure that scientific models, methods and outputs are appropriately presented for the needs of the user. In this perspective, we mention the roadmap followed by the Italian Civil Protection, who has progressively adapted the Emergency Plan designed for Vesuvius (Italy), from a deterministic scenario, originally, to nowadays considering probabilistic analyses. In particular, in the most recent update of the Vesuvius Emergency Plan (<https://www.protezionecivile.gov.it/en/approfondimento/update-national-emergency-plan-vesuvius/>), the reference scenario has been selected on the basis of probabilistic evaluations of the probability of occurrence of different eruptive sizes: the decision has been to take a sub-Plinian VEI 4 event as reference, which has a conditional probability of occurrence, given eruption, slightly below 30%. Hence, the current reference scenario is neither the most likely (which would be a VEI 3, with a conditional probability of about 70%, given eruption) nor the largest expected (a VEI 5, with a conditional probability about 1%). Nevertheless, it represents a “reasonable choice in terms of acceptable risk” (<https://www.protezionecivile.gov.it/en/approfondimento/update-national-emergency-plan-vesuvius/>).

gov.it/en/approfondimento/update-national-emergency-plan-vesuvius/). Similarly, the definition of the “yellow area” (i.e., the area that, in case of eruption, is exposed to significant tephra fallout, but not necessarily to pyroclastic density currents) at Vesuvius and Campi Flegrei is now based on the hazard maps highlighting where an accumulation of 300 kg/m² of tephra fallout has a 5% exceedance probability in the event of an eruption of sub-Plinian type.

It is worth stressing here that the choice of what is an “acceptable risk” can vary enormously from place to place, as well as in time at the same place. Having probabilistic volcanic hazard assessments enables different choices to be made and documented quantitatively, depending on the local/regional/national and temporal contexts (e.g. Newhall and Hoblitt 2002; Aspinall et al. 2003; Selva et al. 2012a, b; Papale 2017; Pallister et al. 2019a; Tierz 2020).

Knowing the differences among hazard and risk assessment approaches related to different hazardous phenomena, and assets, will eventually help to establish a common framework covering terminology, set of methodologies, risk metrics, data needs and results required for further treatment of risk. For most natural hazards, the science can, at the moment, provide advice for risk assessment in a single-hazard framework. A few attempts to compare across volcanic hazardous phenomena are available (e.g., Neri et al. 2013), and there are few more advanced risk assessments considering more than one hazardous process, hazard interactions or even vulnerability interactions. In order to advance vulnerability studies in particular, concerted efforts to gather harmonized damage and loss data are needed (Deligne et al. 2021). Developing capabilities in eruption forecasting and probabilistic volcanic hazard assessment worldwide also needs to be accompanied by increased understanding of risk drivers and the capacities needed to reduce volcanic risk at all scales.

Even moderate-sized volcanic eruptions can cause global impacts (e.g. Eyjafjallajökull 2010, Iceland; Petursdottir et al. 2020) and large-magnitude volcanic eruptions (e.g. Tambora

1815 and Krakatau 1883, Indonesia; Katmai 1912, USA; Pinatubo 1991, Philippines) are capable of causing global cooling over months to years, and can also affect climate change (e.g. Raible et al. 2016). Our globalized society, already suffering from the impacts of climate change, is increasingly vulnerable to such events and more collaborative efforts to plan and prepare for such events, including robust probabilistic volcanic hazard assessments, are needed.

7 Conclusions and Future Directions

In this chapter, we have reviewed the state-of-the-art in eruption forecasting and probabilistic volcanic hazard assessment. We have seen that both these tasks are strongly tied to uncertainty, and that uncertainty depends both on the intrinsic randomness of volcanic processes (aleatory uncertainty) as well as on the data and information available and, thus, on our ‘degree of ignorance’ about such processes leading to eruptions and volcanic events (epistemic uncertainty). We have also seen how to mathematically represent these two types of uncertainty, and what types of information are used in their quantification.

Which data will be used depends on the type of assessment we are interested in, so we have divided the topic into long-term and short-term assessments. We have reviewed what types of models are mostly used for eruption forecasting and volcanic hazard assessment, in the long- and short-term, and at different spatial scales.

As final words, we can say that eruption forecasting and volcanic hazard assessment strongly rely on data and models. The availability of data influences our degree of knowledge or ignorance, which is further complicated by huge variations in the timescales of volcanic processes (from fractions of seconds in fragmentation processes to hundreds of thousands to million years for processes linked with magma generation and storage at depth). The long timescales associated with the lifetime of volcanoes also hamper our ability to reconstruct volcanic processes from the record that has been left at

each volcanic system worldwide. In this respect, the importance of (open) global databases (e.g., VOTW—Global Volcanism Program 2023; WOVOdat—Newhall et al. 2017; LaMEVE—Crosweller et al. 2012; Global Volcano Model, EPOS, etc.) and the collation of hazard-intensity metrics and hazard parameters into publicly open databases (e.g. ESP databases, by Mastin et al. 2009; Auker et al. 2013; Aubry et al. 2021; FlowDat: Mass Flow Database, Ogburn 2025; DomeHaz, Ogburn et al. 2015; etc.) is crucial, as one of the keys to future improvement of our knowledge as a scientific community (e.g. Pallister et al. 2019a; Tierz 2020). Moreover, the idea that we can learn from analogue volcanoes and use data from them to add information on the volcano we are studying is becoming a reality in hazard assessment thanks to the efforts of putting together global databases (Newhall et al. 2017), and to tools and methods that can use such databases to objectively identify sets of analogue volcanoes (e.g., VOLCANS/PyVOLCANS, Tierz et al. 2019, 2021; hierarchical clustering methods, Burgos et al. 2023). Future research efforts should be targeted at incorporating more ‘dynamic’ sets of analogue volcanoes into the volcanic hazard assessment. For example, using analogues that switch between open- and close-conduit regimes (Marzocchi et al. 2004) and/or accounting for the fact that a volcano may be an analogue for volcano A while it is ‘cone-building’, whereas it could be for volcano B when it is ‘dome-destroying/caldera-forming’ (e.g. Tierz et al. 2019). Likewise, the way different parameters, which may influence analogue selection (e.g. volcano morphology), change as the volcano switches between states could be investigated further (e.g. Belousov et al. 2007; Cioni et al. 2008; Tierz et al. 2019; Burgos et al. 2023). As regards models, a frontier topic is related to the testing of hazard models (e.g. Bebbington 2013; Marzocchi et al. 2021) using local and/or global databases. In terms of models used to simulate volcanic processes with the goal of eruption forecasting and hazard assessment, e.g.

for PDC propagation, one challenge may be to simplify complex models into simpler ones that incorporate the fundamental physics but, at the same time, can be more readily used in PVHA, through the combination of ensembles of scenarios using diverse techniques (see Sect. 5.2). Furthermore, the validation and benchmarking of numerical simulators (e.g. Costa et al. 2016; Esposti Ongaro et al. 2020; Gueugneau et al. 2021) with the goal of applying them to volcanic hazard assessment is a topic that will likely deserve increased attention in the near future.

Acknowledgements We wish to warmly thank the reviewers, Susanna Jenkins and Chris Newhall, for their careful reading and helpful reviews, which greatly improved the manuscript. We are also very grateful to the editors, Corentin Caudron and Zack Spica, for their indefatigable editorial support. Support to PT and SL was provided by the Global Geological Risk Platform of the British Geological Survey NC-ODA grant NE/R000069/1: Geoscience for Sustainable Futures. The research was part of the BGS International NC programme ‘Geoscience to tackle Global Environmental Challenges’, NERC reference NE/X006255/1. Published with permission of the Executive Director of the British Geological Survey (NERC-UKRI).

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Prospects for Forecasting Volcanic Eruptions After Long Repose

Christopher R. J. Kilburn

Abstract

Andesitic-dacitic volcanoes share similar patterns of pre-eruptive unrest when they reawaken after centuries in repose. Thus (1) rates of volcano-tectonic (VT) seismicity follow restricted changes with time before bulk failure in the brittle crust, and (2) phreatic explosions are common before bulk failure. The VT trend suggests that magma ascends to the surface at the end of unrest, whereas phreatic activity suggests that magma had previously reached close enough to the surface to vaporize groundwater. The apparent contradiction in the timing of magma ascent is resolved using two historical case studies from Soufriere Hills volcano on Montserrat: a non-eruptive crisis in 1966 and a pre-eruptive sequence in 1995. The results suggest that pre-eruptive trends are driven by the pressurization of a leaky magma body in crust at near-lithostatic pore-fluid pressures; that the crust fails laterally over the magma body, rather than upwards towards the surface; and that the shallowest level for

a pressurizing magma body coincides with when bulk failure opens a fracture large enough for magma to propagate dykes to the surface. The conditions provide the basis for distinguishing levels of increasing unrest and support the view that seeking deterministic constraints on forecasts of eruption is a realistic ambition.

1 Introduction

Nearly half the volcanoes that have erupted in historical time have reawakened above subduction zones after about 100 years or more in repose (from data in Siebert et al. 2010). Such volcanoes have predominantly andesitic-dacitic compositions and show a restricted range of behaviour before they erupt (Voight 1988; McNutt 1996, 2005; White and McCausland 2016, 2019; Kilburn 2018). Long repose allows a volcanic edifice and underlying crust to heal the magmatic pathway that had fed the previous eruption. Renewed activity thus requires another pathway to be formed between an underground magma body and the surface. This promotes repeatable trends among pre-eruptive signals related to rupture of the crust, notably volcano-tectonic (VT) seismicity and ground movement (Kilburn 2018).

One frequently observed association is for magma to break the surface after hyperbolic

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increases in the rates of VT seismicity and ground movement. First proposed by Voight (1988) as a general trend for forecasting eruptions, the association has been recognised on numerous occasions, when hyperbolic trends have developed over intervals from weeks (Tokarev 1971, 1985; Kilburn and Voight 1998; De la Cruz-Reyna & Reyes-Davila 2001; Kilburn 2003) to years (De la Cruz-Reyna et al. 2008; Robertson and Kilburn 2016) before eruption. The behaviour has been quantitatively linked to the final stages of elastic-brittle rupture under increasing stress (Kilburn 2012, 2018) or during corrosion under constant stress (Kilburn and Voight 1998; Main 1999; Kilburn 2003). Precursory deformation and seismicity describe how fracturing increases before reaching the critical state at which a major new discontinuity can form through the crust. The time to reach critical conditions depends on the rate at which the crust is stretched by a deforming source, which is normally taken to be a body of pressurizing magma several kilometres underground.

The simplest interpretation is that magma ascends from the pressure source after bulk failure. The interpretation, however, is incomplete. Independent field data, such as the occurrence of phreatic explosions, indicate that magma can almost reach the surface before the hyperbolic signal for bulk failure appears (Hoblitt et al. 1996; Gardner and White 2002). Taken together, the seismic and surface precursors suggest that bulk failure is required for magma to break the surface, but not for it to reach shallow levels underground.

The implication is contradictory: if magma has already travelled several kilometres almost to the surface through a newly-formed pathway, why should a subsequent signal for bulk failure be associated with it rising the short additional distance necessary to erupt? The contradiction is investigated here by comparing a non-eruptive and pre-eruptive crisis at Soufriere Hills volcano on Montserrat. The results suggest that precursory sequences are caused by the pressurization of leaky magma bodies. They also indicate that patterns of pre-eruptive behaviour reflect

natural constraints on the evolution of shallow magmatic systems, raising confidence that using deterministic criteria to improve forecasts of eruption is a feasible goal.

2 Eruptions Through Elastic-Brittle Crust

An idealized pre-eruptive sequence begins with crust being stretched over a body of pressurizing magma (e.g., when vesiculation or the injection of new magma causes doming of the overlying carapace, or when tectonic extension occurs above a magma body). As deformation proceeds, the crust's behaviour changes from elastic movement without seismicity, through elastic movement with subordinate fracturing and fault slip (quasi-elastic) to movement by fracturing and faulting alone (inelastic). In the elastic and quasi-elastic regimes, unbroken crust stores an increasing amount of stress as it deforms (Appendix). The transition to inelastic behaviour occurs when the crust is unable to store additional stress, so that further deformation is accommodated by rock fracture under a constant stored stress.

Inelastic failure is not immediate, but requires time for a new network of fractures to create a major discontinuity. The rate of seismicity may be constant while isolated fractures form and grow at the start of inelastic behaviour, but accelerates when the fractures start linking together. The acceleration continues until bulk failure, when the fracture network becomes a single discontinuity. A steady and then accelerating VT event rate thus marks the evolution of a fracture network from birth to bulk failure (Kilburn 2003).

When stress is increased at a constant rate, the accelerations in VT event rate are exponential in the quasi-elastic regime, but hyperbolic (which is faster than exponential) in the inelastic regime (Fig. 1); the contemporaneous rate of ground movement remains approximately constant until, finally, it also increases hyperbolically in proportion with the VT event rate (Kilburn 2018).

When the deforming source is an enclosed body (such as a pressurizing magma chamber),

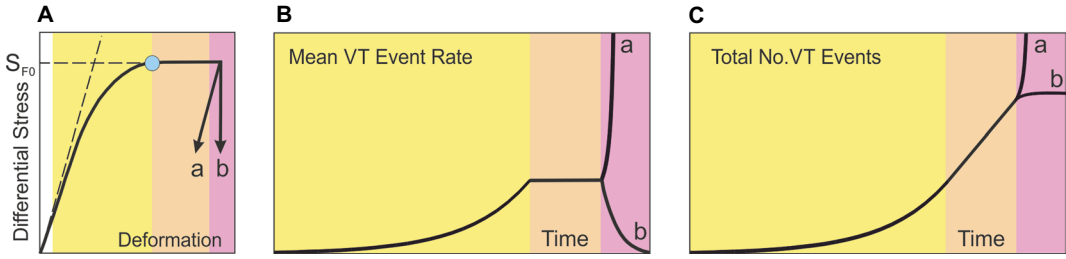


Fig. 1 **A** As the differential stress S_d becomes larger, faulting contributes a greater proportion to the total elastic-brittle deformation; the amount is given by the difference between the observed deformation (*unbroken curve*) and ideal elastic trend (*broken line*). Deformation passes from elastic (*white*), through quasi-elastic (*yellow*) to steady (*peach*) and unsteady (*pink*) inelastic regimes. Inelastic behaviour develops under a constant differential stress, S_{F0} . Stress decays at the end of the sequence either (a) with bulk failure and eruption, during which the crust contracts around the emptying pressure source (shown here as an elastic contraction), or

(b) by relaxing under a bulk strain that remains constant because the pressure source stays intact at a constant volume. **B** Under a constant rate of deformation, the mean VT event rate increases exponentially to a steady value in the quasi-elastic regime, remains constant at the start of inelastic behaviour and then increases hyperbolically to bulk failure or (b) decays as $1/\text{time}$. **C** The VT event rates yield corresponding changes with time in the total number of events, with an exponential increase becoming linear and then increasing (a) with $\ln [1 - (t/\tau)]$, where τ is the timescale of acceleration, or (b) with $\ln (t/t')$, where t' is the timescale of decay

the total strain it induces in the crust is maintained unless its volume is reduced (e.g., as a result of magma escape during eruption). Hence, if a magma body stops pressurizing before bulk failure, the crust may release some of its stored stress by slipping back along faults while keeping the total strain the same. Such behaviour favours a rate of seismicity that decays inversely with time, following a form similar to Omori's law for earthquake aftershocks (Ojala et al. 2004; Mogi 2007).

2.1 Quantifying Elastic-Brittle Deformation

Readers less interested in quantitative descriptions can go straight to the next section. Progress through the deformation regimes is described quantitatively by relations that connect changes in the differential stresses supplied to the crust (S_{sup}) by the pressure source, lost by faulting (S_L), and stored in the crust (S_d ; Kilburn 2018). They show how the exponential, constant and hyperbolic trends occur naturally when stress is supplied to the crust at a constant rate (Fig. 1). Thus a stress balance gives

$$S_d = S_{\text{sup}} - S_L \quad (1)$$

and an energy balance for deformation in extension leads to

$$dN/dt = (dN/dS_L) (dS_{\text{sup}}/dt) \exp(-\Delta S/\sigma_T) \quad (2)$$

where N is the number of detected VT events, ΔS is the additional stress necessary for bulk failure and σ_T is the tensile strength of the crust. The tensile strength is constant for a particular sequence and, if the same population of faults controls stress loss throughout deformation, then dN/dS_L is also constant. In the quasi-elastic regime, $\Delta S = S_{F0} - S_d$ and $S_d \propto S_{\text{sup}}$, so that $dN/dt \propto (dS_{\text{sup}}/dt) \exp(S_{\text{sup}}/\sigma_T) \propto (dS_{\text{sup}}/dt) \exp(S_d/\sigma_T)$. When the rate of stress supply is constant, S_d increases at a constant rate ($dS_d/dt = \text{constant}$) and so the event rate increases exponentially with time as $dN/dt \propto \exp(t/t_{\text{ch}})$, where the characteristic timescale $t_{\text{ch}} = \sigma_T/(dS_d/dt)$. The stored stress increases until it reaches S_{F0} , at which stage the crust enters the inelastic regime and maintains the same differential stress (S_{F0}) until bulk failure. Hence, for deformation starting with a relaxed crust ($S_d = 0$), the value of $t/t_{\text{ch}} = S_{F0}/\sigma_T$ at the end of trend.

In the inelastic regime, ΔS measures rearrangements in local stress as values increase at the tips of discontinuities but decrease along their margins. The rearrangements occur while the mean stress for the crust remains the same (Fig. 1). Initially, the net change is negligible, so that $\Delta S \approx 0$ and dN/dt is constant for a steady supply rate. Later, the local stresses become increasingly concentrated at the tips of discontinuities and $\Delta S = \gamma^* \sigma_T N$, where γ^* denotes the amount of stress rearranged by each step in the growth of the fracture network (Kilburn 2018). For a constant value of γ^* , the event rate becomes $dN/dt \propto \exp(\gamma^* N) \propto (1 - t/\tau)^{-1}$, which describes a hyperbolic increase in event rate over a time interval $\tau = 1/[\gamma^*(dN/dt)_{h0}]$ starting from an event rate of $(dN/dt)_{h0}$.

Relations (1) and (2) support the interpretation that elastic-brittle deformation controls styles of precursory unrest after long repose. In addition to describing the exponential, steady and hyperbolic increases in VT event rate, they yield values for S_{F0}/σ_T at the transition from quasi-elastic to inelastic behaviour and for γ^* during the final approach to bulk failure. The terms can be used to test the physical plausibility of the trends. For failure in tension $S_{F0}/\sigma_T \leq 4$ (Fig. 2; Shaw 1980) and

$$\gamma^* = B(S_{F0}/\sigma_T)^2(\sigma_T/E) \quad (3)$$

where E is the crust's Young's modulus of elasticity and B describes the shape of the new fractures (Kilburn 2018). The ratio σ_T/E gives the bulk strain at failure and is $\sim 10^{-4}$ for intrusive

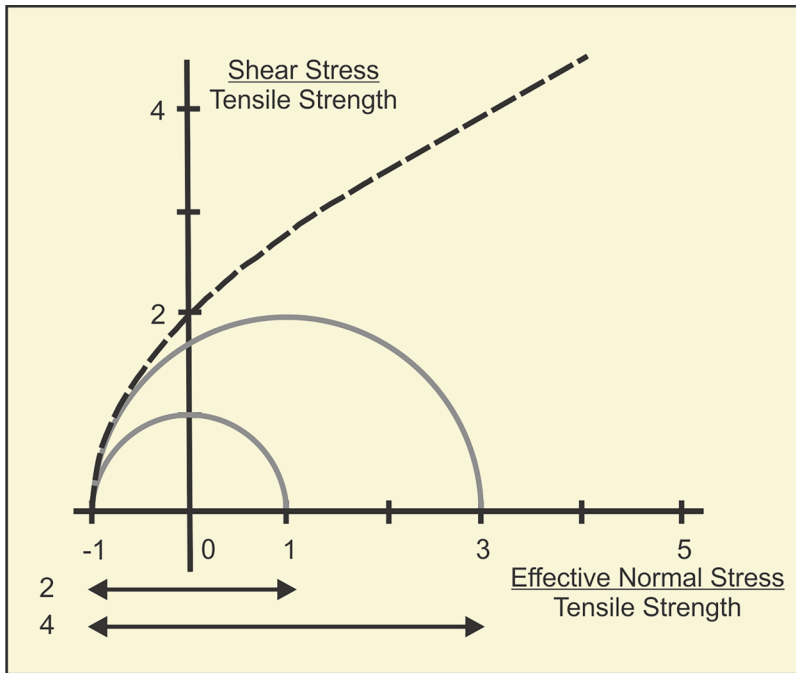


Fig. 2 The Mohr-Coloumb-Griffith criterion (*broken curve*) shows the combinations of effective normal and shear stress that permit bulk failure (Secor 1965; Shaw 1980; Sibson 1998). The axes have been normalised against the tensile strength. Normal stresses are positive in compression and negative in tension. Tensile failure occurs when the minimum effective normal stress equals the crust's tensile strength, or when the

[Effective Normal Stress]/[Tensile Strength] is -1 . The Mohr circles (*continuous semi-circles*) describe states of stress between the maximum and minimum effective normal stresses. The diameter of a circle gives the ratio S_d/σ_T . The largest circle that can meet the failure envelope (when S_d becomes S_{F0}) has a value of $S_{F0}/\sigma_T = 4$. Conditions for failure when $S_{F0}/\sigma_T = 2$ are shown for comparison

magmatic rocks (Huang et al. 2021), while B takes the values of π for a straight-edged fracture (effectively growing in one direction with a long leading edge) and $4/\pi$ for a fracture with a circular margin growing in two dimensions (Lawn 1993). The representative values yield $\gamma^* \sim 10^{-3}$ – 10^{-2} per event for typical crustal properties. The theoretical ranges for both S_{F0}/σ_T and γ^* are consistent with field data (Kilburn 2018).

3 Natural Controls on Precursory Behaviour

The exponential, steady and hyperbolic time series occur when the rate of pressurization on the crust is constant. The constraint is not imposed by the theoretical analysis (Eq. (2)), but emerges from the behaviour of volcanoes themselves. For example, a constant rate of pressurization may reflect a steady rate of magma transport into the pressure source; steady flow, in turn, coincides with minimum rates of mechanical energy loss from a moving fluid. Volcanic systems may thus have a natural

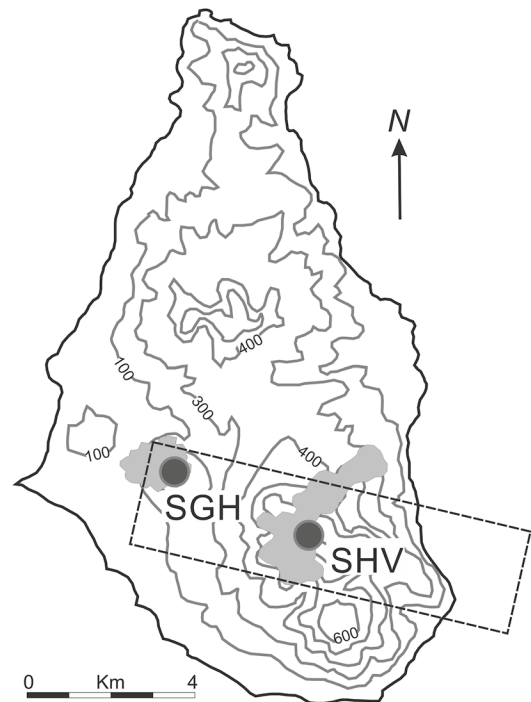
tendency to minimize energy dissipation during magma transport (Kilburn 2018).

In addition to their value for forecasting eruptions, therefore, precursory signals offer insights into the broader controls from Nature that guide volcanic behaviour. Such types of control may explain why eruptions at reawakening volcanoes are associated with bulk failure in the crust, even though magma may have virtually reached the surface beforehand. The action of such controls is explored here by comparing two unrest sequences from the Soufriere Hills volcano in Montserrat, one of which ended with a VT crisis and the other with an eruption.

4 Volcanic Unrest and Eruption at Soufriere Hills, Montserrat

The Soufriere Hills volcano on Montserrat (Fig. 3) belongs to a chain of andesitic-dacitic volcanoes on the Lesser Antilles subduction zone, where the North Atlantic Plate is subducting westwards beneath the Caribbean Plate

Fig. 3 Epicentres of VT seismicity on Montserrat were concentrated within the rectangle in 1966 (Shepherd et al. 1971) and the grey zones in 1995 (Aspinall et al. 1998). The contours are at irregular intervals in metres above sea level. Spot heights are 914 m for Chance's Peak, on the rim of pre-1995 crater of Soufriere Hills volcano (SHV), and 361 m for St George's Hill (SGH)



(Lindsay et al. 2005; Wessels 2019). It reawakened in 1995 after 350 years or more in repose. The eruption was preceded by a year of continuous unrest. The unrest was the fourth episode to have occurred at approximately 30-year intervals. The three previous episodes occurred in 1897–1898, 1933–1937 and 1966–1967 (MacGregor 1938; Powell 1938; Perret 1939; Shepherd et al. 1971; Wadge and Isaacs 1988) and have been attributed to intrusions of magma (Shepherd et al. 1971; Zellmer et al. 2003).

4.1 Unrest Without Eruption, 1966–1967

The following summary of the 1966–1967 unrest is based on observations by Shepherd et al. (1971). The first signs of unrest were two felt earthquakes in January 1966 and another eight in February. Four seismometers were installed between 22 March and 29 April that could register events with magnitudes greater than 2; the largest recorded magnitude was 4. The rate of VT seismicity accelerated during this interval before settling to a constant mean value of 3 events per day during May and the first week of June (Fig. 4). The mean rate then declined until only sporadic events were detected after mid-November (Fig. 4). The sequence of nearly continuous recorded seismicity lasted for about 230 days and was followed the next year by a cluster of about 50 events between August and December. The earthquakes were concentrated within a WNE-ESE band, 14 km long and 4 km wide, that passed across the summit of Soufriere Hills (Fig. 3). About 80% occurred within 2 km of the volcano at depths of between 1 and 7 km and a small number of deeper events reached to 16 km. Meanwhile, at Galway's Soufriere, a fumarolic zone about 1 km south of the volcano's summit, the unrest was marked between May and October 1966 by a two-fold increase in heat flow to nearly 5×10^5 W and a temperature increase by at least 11–109 °C. These changes, combined with the shallow depths of VT events, led Shepherd et al. (1971)

to conclude that “a relatively small volume of magma originating from a depth of greater than 10 km was injected into a complex system of cracked and fissured rock immediately below the Soufriere Hills.”

The daily number of VT events remained about 5 or less for 87% of the main period of unrest between 23 March and 09 November (202 of 231 days); for the rest of the time, the daily number was between 6 and 25 events, apart from a swarm of about 61 VT events on 21 August (Fig. 4). Across the whole sequence, the mean event rate changed with time in three stages (Fig. 4): (1) an exponential increase proportional to $\exp(t/15.7)$ between 23 March and 02 May; (2) a steady rate at about 20 events every five days for 03 May–07 June; and (3) excluding the swarm of 21 August, a decrease with time from mid-June onwards, proportional to $258/t$ (all times in days). Although values during the first two best-fit trends may have been affected by upgrades to the monitoring network, the overall VT pattern follows the trend expected for quasi-elastic behaviour until the beginning of May, followed by steady inelastic movement until mid-June and then an Omori-style decay. The fracture sequence is thus consistent with the intrusion of magma until June 1966 and the subsequent relaxation of stress in the crust until the end of the year.

4.2 Unrest and Eruption, 1995

The 1995 unrest was heralded by occasional swarms of local volcano-tectonic (VT) seismicity between 1992 and 1994, most at depths of 6–15 km (Aspinall et al. 1998; Robertson et al. 2000; Shepherd et al. 2002). Persistent unrest started in January 1995 and continued for about 274 days with VT seismicity at depths of less than 6 km (Aspinall et al. 1998; Shepherd et al. 2002). They suggested a pressure source about 6–7 km below the summit (Aspinall et al. 1998), consistent with the petrology of the first products to be erupted (Barclay et al. 1998; Devine et al. 1998, 2003).

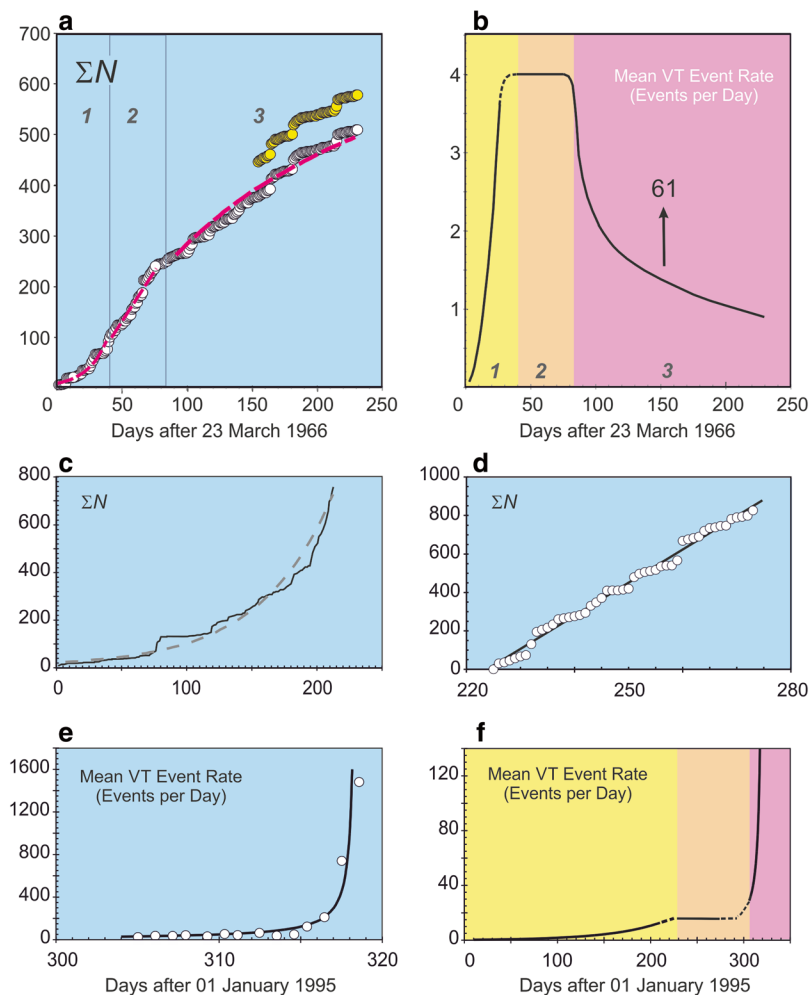


Fig. 4 a–b 1966 seismic crisis at Soufriere Hills volcano. **a** The total number of VT events ΣN with time t in days. The trend is broken by an abrupt jump (yellow circles) caused by a seismic swarm of c. 61 events on 21 August (Day 151). When this is removed (white circles), the underlying ΣN - t trend changed: (1) exponentially, $\Sigma N = A_2 + 8.3 \exp(t/15.7)$, (2) linearly, $\Sigma N = A_3 + 4.1t$, and (3) logarithmically, $\Sigma N = A_4 + 258 \ln t$ (where the A -terms denote values of ΣN at the start of each trend); the corresponding mean event rates are proportional to (1) $\exp(t/15.7)$, (2) 4.1, and (3) $258/t$. The best fit equations are for the zones labelled 1–3. **b** Changes in mean VT event rate reconstructed from the best-fit trends

in (a). The background colours show the deformation regimes described in Fig. 1. The arrow marks the omitted seismic swarm of c. 61 events on Day 151). **c–e** Field data for changes in VT seismicity during pre-eruptive unrest at Soufriere Hills in 1995. Data are from Shepherd et al. (2002) for (c), Gardner et al. (2002) for (d), and Kilburn and Voight (1998) for (e). Corresponding best-fit trends give $\Sigma N = 16 \exp(t/55.6)$, $\Sigma N = A_5 + 17t$, and $dN/dt = 27[1 + (t - t_{h0})/15.4]^{-1}$ where t_{h0} is the time when the hyperbolic trend began (Kilburn 2018). **f** Changes in mean VT event rate reconstructed from the best-fit trends in (c–e). The background colours show the deformation regimes described in Fig. 1

The earthquakes were recorded by a network of at least five seismometers (Aspinall et al. 1998). They occurred within the same region as in 1966 (Fig. 3), but were more focussed in an approximately cylindrical volume 2 km across beneath the volcano, with a linear offshoot, about 3 km long and 1 km wide extending to the NE, and a separate cylindrical volume 2 km wide beneath St George's Hill, about 4 km to the NW (Aspinall et al. 1998). Seismicity continued beneath Soufriere Hills throughout the sequence, but diminished with time under St George's Hill (Aspinall et al. 1998).

The range of recorded magnitudes was similar to that in 1966–1967. Most of the events had local magnitudes between 1.7 and 2.5 (Power et al. 1998), corresponding to slip along faults less than 0.2 km across (McNutt 2000), although occasional events reached magnitudes of 4 and implied lengths of about 1.7 km (Power et al. 1998; McNutt 2000). The VT precursors were thus dominated by the movement of faults much smaller than the several kilometres of the new pathway for magma ascent. Movements beneath the volcano itself indicated normal faulting (Aspinall et al. 1998), consistent with crust being stretched over a pressure source.

Additional precursors began with phreatic explosions on 18 and 25 July, about two-thirds of the way through the VT sequence; they recurred on most days throughout August, but only occasionally thereafter (Young et al. 1998; Gardner and White 2002). They were accompanied by high outputs of volcanic SO₂, which fluctuated from 300 to 1200 tonnes per day before declining during the second half of August, describing a pattern consistent with the degassing of shallow magma (Gardner and White 2002).

The full VT time series describes the idealized sequence to bulk failure before eruption in mid-November. From the start of January 1995 (Fig. 4), the mean VT event rate increased exponentially for about 212 days (Shepherd et al. 2002), before settling in July to 48 days at an approximately constant value of 17 events per day (Gardner and White 2002) and then to a 14-day hyperbolic increase until 15 November,

when rates were greater than 1,200 events per day and a new lava dome broke the surface (Kilburn and Voight 1998). Both of the accelerating trends are quantitatively consistent with tensile failure. First, the exponential VT trend had a characteristic timescale of 55.6 days (Kilburn 2018) and so a value for S_{F0}/σ_T at the end of the trend in July of 3.8 (212/55.6), within the range for the onset of bulk failure. Second, the hyperbolic trend in November had a value for γ^* of 2.4×10^{-3} per event, again within the range expected for bulk failure in tension (Kilburn 2003, 2018). From Eq. (3), the strain at failure is $(\gamma^*/B)(\sigma_T/S_{F0})^2$, which yields 0.5×10^{-4} and 1.6×10^{-4} respectively for fractures with straight and circular edges. Although both are close to the notional value of $\sim 10^{-4}$ (Huang et al. 2021), the magnitudes favour the two-dimensional spreading of a fracture behind a curved margin.

5 Fracturing and Eruption

The VT events at Soufriere Hills in 1966 and 1995 share several features:

1. Their magnitudes were less than 4 (down to instrumental threshold values of 1.7 and 2).
2. Their hypocentres were concentrated at depths of less than 7 km.
3. Their sequences continued for comparable durations of c. 230 and 274 days.
4. The VT sequences opened with accelerating and then steady mean VT event rates.
5. The steady VT rates were accompanied by increased fumarolic or phreatic activity (after May 1966 and July 1995 respectively).

The first two features suggest that VT seismicity was determined by slip among similar small faults in an elastic-brittle crust; the third that unrest was driven by a similar type of pressurizing source; and the fourth that deformation evolved from the quasi-elastic to inelastic regimes. The fifth feature indicates that magma-filled fractures reached depths shallow enough to heat fumarolic fluids and, in the extreme,

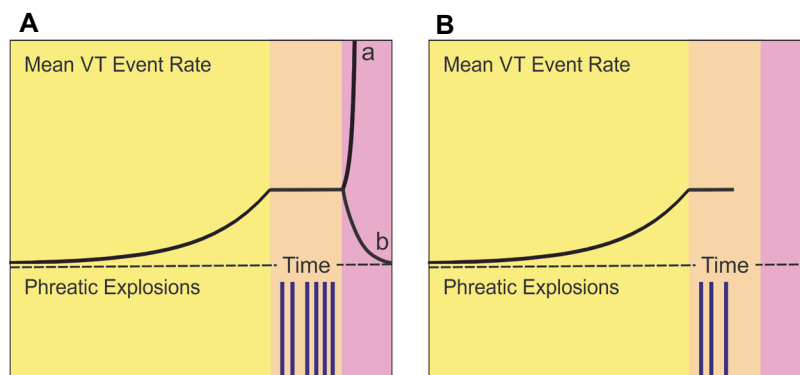


Fig. 5 A Soufriere Hills' VT sequences in 1966 and 1995 show evidence of heated surface fluids or phreatic explosions when the event rates are steady, regardless of whether the following rates (a) increase or (b) decay. Their appearance coincides with the start of inelastic behaviour, which suggests (1) that initial fracturing before bulk failure produced one or more fractures large enough to allow the propagation of dykes from

the pressure source into the volcanic edifice and, hence, (2) that the pressure source is a magma body. As shown in Fig. 9, the combination of VT seismicity and surface phenomena allows five levels of unrest to be recognised. B The opening of a low-flank vent or flank collapse may permit dykes to reach the surface and start an eruption before bulk failure. In such cases, eruptions will occur without a hyperbolic increase in VT event rate

to trigger phreatic explosions by vaporizing groundwater (Fig. 5). It also indicates that the pressurizing source was a magma body and that the propagation of dykes was favoured when the crust entered the inelastic regime of deformation, possibly with more than one episode of ascent promoting the intermittent timing of the phreatic explosions in 1995 (Gardner and White 2002). All the features together are consistent with new fractures opening around the margins of a pressurizing magma body. The fractures were large enough for magma to leak upwards, but not to reach the surface. Only in 1995 did magma erupt, after the VT event rate had increased hyperbolically along the trend expected during the final approach to bulk failure.

A requirement for bulk failure before eruption is remarkable. Such failure marks the growth of the largest discontinuity in a pressurization sequence. It is not a local phenomenon restricted to the margins of a dyke, but a system-wide process that allows the deforming crust to relax its accumulated stress. In tension, for example, previous stretching is reduced as the surfaces of a new rupture separate. Fracturing below a volcano is expected to start close to the

pressurizing magma, where it induces the largest differential stress in the crust (Gudmundsson 1998, 2011). The new fractures grow within a plane perpendicular to the direction of induced tension and so a new discontinuity is most likely to run either vertically to the surface, or laterally across the roof of the pressure source (Fig. 6). A completely new rupture vertically is unlikely given that magma had already been arriving at shallow depth. The VT signal of bulk failure is thus more likely to reflect the growth of a lateral rupture and relaxation of crust around the pressurized magma body. Apparently, therefore, the ability for magma to reach the surface coincides with relaxation around the pressure source after bulk failure.

Relaxation and eruption are not an obvious cause and effect. A simpler explanation is that they are both the product of a condition not previously achieved in the magmatic system. Fractures formed during inelastic deformation create a longer and wider discontinuity as they link together (Fig. 6). The contemporaneous propagation of dykes shows that (1) some of the narrow fractures can pierce the roof of the pressure source and (2) the source pressure is large enough to propagate dykes (Fig. 6). The ideal

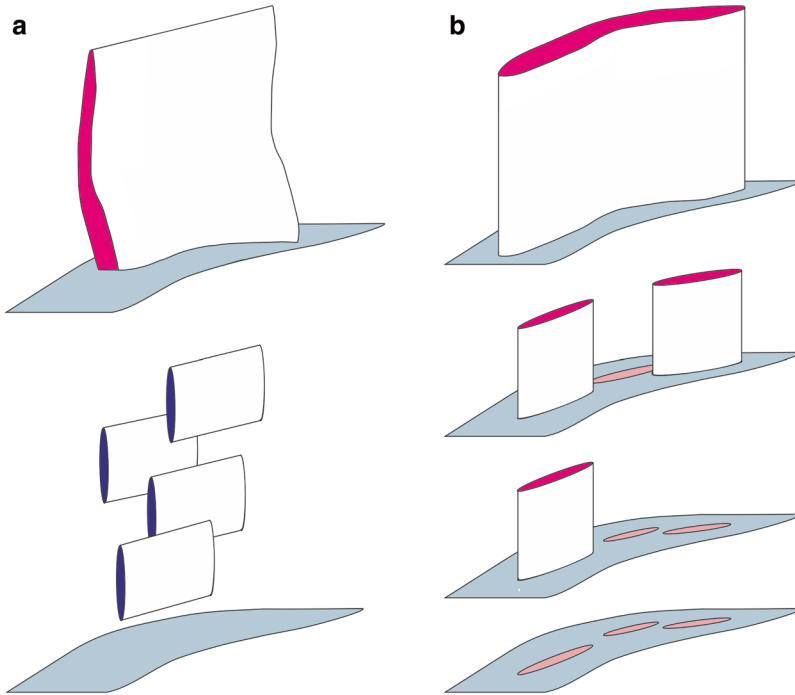


Fig. 6 Growth of fractures before bulk failure. **a** *Bottom.* Initial fractures open in the crust above the margin of the source magma body (*pale blue*). *Top.* The fractures link to form a major discontinuity that penetrates the magma body and allows a dyke to propagate to the surface. **b** *From bottom to top.* Initial fractures (*pink*) open across the margin of the magma body. Some fractures become large enough for dykes to propagate

(only one is shown here); the dykes are too small to reach the surface. The fractures grow and link together, until bulk failure produces a major discontinuity that is large enough for a new dyke to reach the surface. Only Sequence B is consistent with the arrival of magma into a volcanic edifice before bulk failure and eruption (see also Fig. 7)

amount of ascent is attained when the upward driving pressure is balanced by the downward pressure from the weight of magma in the dyke; hence a first requirement for eruption is that the ideal length is greater than or equal to the distance between the pressure source and the surface. Magma also solidifies during ascent as a result of losing heat to the crust (Rubin 1995; Acocella 2021) and of degassing-induced crystallization (Gardner and White 2002; Couch et al. 2003); a second requirement for eruption, therefore, is that magma is able to reach the surface before it has had time to solidify.

Potential limits to the ascent rate of a magma-filled fracture are the rate of opening of a new pathway ahead of the fracture and the velocity at which the magma rises through the

fracture. Assuming that the second constraint has the greater influence (Parfitt and Wilson 2008), a first-order estimate for the time T for steady magma ascent gives (Appendix):

$$T \gg (\mu/\Delta P)(L/X)^2 \quad (4)$$

where μ is magma viscosity, ΔP is the source overpressure, and L and X are the length and gape of the fracture.

Equation (4) is consistent with conditions at the start of the 1995 eruption at Soufriere Hills (Appendix). For a source 6 km below the surface, petrological data indicate ascent times of about 6×10^6 s or 8–9 weeks (Devine et al 1998). Notional average viscosities for the andesite magma are 1–10 MPa s (Melnik and Sparks 2002), $L/X \sim 10^3$ and $\Delta P \approx 20$ –30 MPa

(determined from $S_{F0}/\sigma_T = 3.8$ at failure and the geometry of the source; Appendix). The right-hand side of Eq. (4) is thus $\sim 10^6$ – 10^7 s, which agrees with the petrological estimate.

Although approximate, Eq. (4) shows that, for a given magma and source depth (μ and L fixed), the time for ascent is smaller for larger driving pressures and wider fractures (because they offer a lower rheological resistance to flow). Hence, the coincidence between bulk failure and eruption can be attributed to when the combination of driving pressure and fracture width first exceeds the threshold needed for magma to reach the surface. Growth of a

fracture network around the pressure source will thus favour a succession of dykes extending higher into the volcanic edifice before finally reaching the surface—and such a succession can naturally account for the repeated episodes of increased fumarolic activity and phreatic explosions observed ahead of a magmatic eruption (Fig. 6).

An eruption can occur only if the pressure source is sufficiently close to the surface (Fig. 7). If it is too deep, it will feed an intrusion and the magmatic system will have to establish a new and shallower source of pressurization to produce an eruption. Once a pressure source has

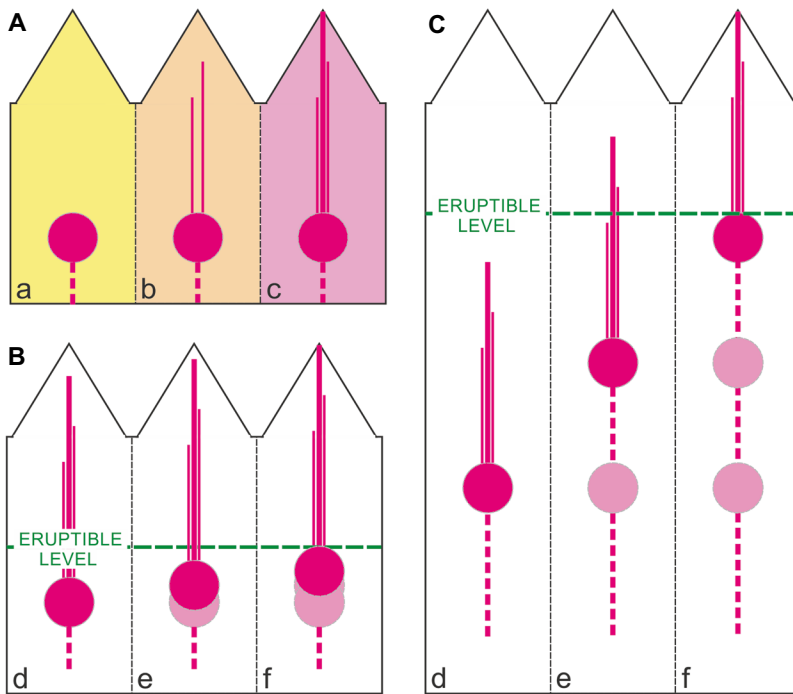


Fig. 7 **A** The pressurizing magma body increases the stress on the surrounding rock in the quasi-elastic regime (a). Inelastic behaviour begins when the effective normal stress acting around the margin reaches the crust's tensile strength, which also establishes the failure differential stress S_{F0} (Fig. 2). Fractures open that are large enough for magmatic dykes to almost reach the surface (b). At bulk failure across the margin (c), the fractures link to form a larger discontinuity from which a dyke can propagate to the surface (Fig. 6). The background colours follow the deformation regimes in Fig. 1. **B** If the magma

body is too deep (f), the dyke from bulk failure may not be able to reach the surface. Magma stalls and creates another zone of magma accumulation at shallower level. The process is repeated (e) until the magma body reaches the “eruptible level” (f), which coincides with the deepest level at which a dyke can reach the surface after bulk failure. Once this stage is reached, the magmatic system no longer needs to create an even shallower pressure source, because magma has already been able to erupt. **C** Illustrating (B) with a greater upward displacement of the magma body

formed at the deepest “eruptible” level, an even shallower source is not necessary because eruptions relieve the accumulated overpressure.

6 Pore-Fluid Pressure Around Magmatic Systems

The condition that $S_{F0}/\sigma_T \leq 4$ for tensile rupture reveals that bulk failure must occur when pore-fluid pressures in the surrounding crust are close to lithostatic values. The differential stress imposed by a pressurizing magma body is the difference between the effective compression acting perpendicular to its surface and the tension acting around it. As described in the Appendix, for a given depth and shape of magma body, the magnitude of S_{F0}/σ_T increases with magmatic overpressure (the difference between magmatic pressure and the pressure in the crust before pressurization starts), but decreases with increasing pore-fluid pressure.

The failure conditions are shown in Fig. 8 for the simplified examples of a pressurizing sphere and vertical cylinder in crust which had a lithostatic pressure distribution before deformation. Field data for Soufriere Hills in 1995 (Kilburn

and Voight 1998; Gardner and White 2002; Shepherd et al. 2002) give 3.8 for S_{F0}/σ_T at the start of the inelastic regime (Kilburn 2018) and 6–7 km for the depth of the pressure source (Aspinall et al. 1998). The values together yield pore-fluid pressures approaching 95% of the lithostatic value for a cylinder and exceeding 98% for a sphere.

The result supports previous proposals that nearly lithostatic pore-fluid pressures must be available in the crust for a magma reservoir to rupture in tension (Shaw 1980; Gerbault 2012; Grosfils et al. 2013; Albino et al. 2018). It is not clear, however, whether high pore-fluid pressures occur through whole sections of the crust, as has been found in locations without active volcanoes (Hillis 2003), beneath local horizons where processes such as mineralization have reduced the permeability of the crust (Hurwitz and Lowenstern 2014), or whether they are generated only in the vicinity of reservoirs by magma bodies themselves—for example, by locally compressing and heating the surrounding rock (which may seal cracks and reduce permeability) and by releasing volatiles into the crust (Newhall et al. 2001; Jamtveit et al. 2004).

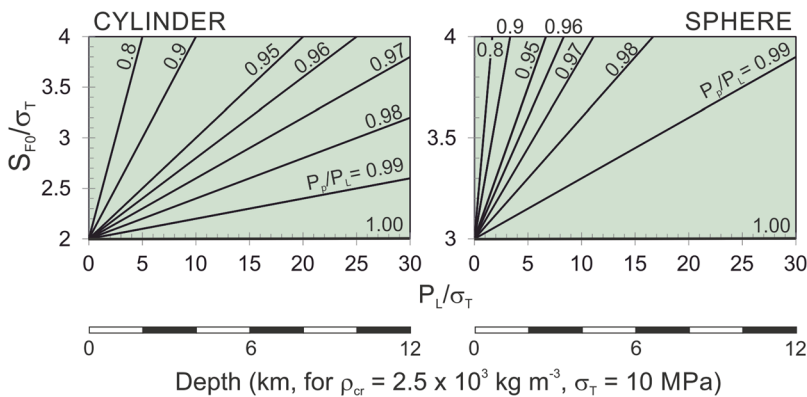


Fig. 8 The stress ratio S_{F0}/σ_T at bulk failure around a pressure source depends on the geometry of the source, lithostatic pressure P_L (and hence depth from $P_L = \rho_{cr}gz = [\text{mean crustal density}] \times [\text{gravity}] \times [\text{depth}]$), and the ratio P_p/P_L of pore-fluid to lithostatic pressure. The graphs show conditions for bulk failure around a cylindrical (*left*) and spherical (*right*) pressure

source (Eqs. (8) and (9)). For the top of a pressure source at a depth of 6–7 km (c. 15 MPa for $\rho_{cr} = 2.5 \times 10^3 \text{ kg m}^{-3}$ and $\sigma_T = 10 \text{ MPa}$) and a value of 3.8 for S_{F0}/σ_T at Soufriere Hills in 1995, the implied pore-fluid pressure approaches 95% of the lithostatic load around a cylinder and exceeds 98% around a sphere

7 Forecasting Eruptions

Pre-eruptive signals similar to those at Soufriere Hills have been observed at numerous andesitic, subduction-zone volcanoes reawakening after long repose (McNutt 1996; De la Cruz-Reyna et al. 2008; White and McCausland 2016; Kilburn 2018). Their repeatability is consistent with self-regulating magmatic systems, for which bulk failure presents the conditions necessary for magma to reach the surface: an eruption occurs when the depth of a new zone of magma storage is the same as the maximum length of dyke that it can propagate; the maximum length is governed by the widest rupture across the storage zone; and the widest rupture is produced by bulk failure.

The failure sequence is monitored instrumentally and, for a magmatic source being pressurized at a constant rate, leads to VT event rates that change with time from exponential to steady to hyperbolic. Evidence of heating at the surface provides qualifying information that magma is a probable cause of the unrest. Phreatic explosions, in particular, indicate that pre-failure dykes have been able to extend close enough to the surface to turn groundwater into steam.

The instrumental and visual changes together offer a framework for identifying combinations of precursory signals that can be expected during a potential pre-eruptive sequence. For example, five levels of unrest can be recognised from the sequences seen at Soufriere Hills (Fig. 9):

- Level 1. Exponential increase in VT event rate with time.
- Level 2a. Steady VT event rate (when following an exponential increase).
- Level 2b. As for Level 2, but with heated surface fluids, such as fumaroles.
- Level 2c. As for Level 3, but with phreatic explosions.
- Level 3. Hyperbolic increase in VT event rate.

Level 1 corresponds to quasi-elastic deformation, Levels 2a–c to the onset of inelastic behaviour and the propagation of dykes into

the volcanic edifice, and Level 3 to the final approach to bulk failure. All three intermediate levels (2a–c) can progress directly to Level 3, without passing through an intervening level. Their characteristic signal is the change from accelerating to steady rates of VT seismicity. Given that change, the appearance of stronger surface phenomena—from hotter fumaroles to phreatic explosions—reinforces the interpretation that a magmatic eruption may be approaching. However, an absence of the surface phenomena cannot be taken to mean that a magmatic eruption is unlikely. Indeed, a crucial feature of the intermediate levels is that constant rates of seismicity are not indicators of stability, especially when they follow an interval of accelerating rate: instead, they represent a preliminary stage to bulk failure and so point to an increased potential for eruption.

The levels have different relative uncertainties attached to their forecasts (Fig. 9). As illustrated by the behaviour of Soufriere Hills, magma escape from a pressuring source is expected once the crust has started to deform inelastically and an eruption is expected after bulk failure has occurred. Following the trends expected from the elastic-brittle model (Fig. 1), evidence of quasi-elastic behaviour suggests that an eruption is unlikely, whereas hyperbolic increases in VT rate suggest that one is more likely, although still not guaranteed. In contrast, the steady stage of inelastic behaviour is consistent with a possible eruption, but also with a decline in unrest. The confidence of forecasts is thus highest when VT event rates increase with time, but lowest when the rates appear steady.

Uncertainty during steady VT seismicity is especially acute when a monitoring network first becomes operational after deformation has entered the inelastic regime (Fig. 9). In this case, the steady rates may be mistaken for the early stages of quasi-elastic behaviour *before* its expected accelerating form has become evident. The error will only be apparent with evidence of heated fluids or the onset of a hyperbolic increase in VT event rate; in other words, increased unrest will appear to start at Levels 2b, 2c or 3.

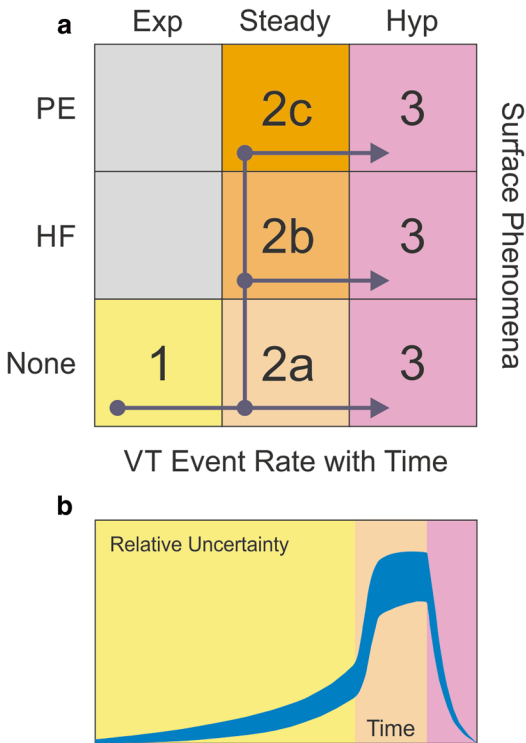


Fig. 9 **a** Five levels of unrest can be distinguished by combining VT trends for the three stages of elastic-brittle deformation (quasi-elastic (yellow), steady inelastic (peach, light and dark orange) and unsteady inelastic (pink)) and the strength of surface phenomena (none, heated fluids HF, and phreatic explosions PE). The threat increases from Level 1 to 3. The arrows show three potential sequences, 1-2a-3, 1-2a-2b-3, and 1-2a-2b-2c-3 according to nature of the surface phenomena observed during steady VT seismicity in the inelastic regime (see text for details). In this example, the combinations in grey are considered to be physically unlikely. **b** The amount and range of relative uncertainty on the outcome of unrest are largest when VT event rates are steady in

the inelastic regime (peach); they reflect uncertainty about whether the steady VT rates will increase hyperbolically to eruption or decay without magma reaching the surface; heated fluids and phreatic explosions reduce the uncertainty that an eruption is possible. The amount and range of uncertainty are lower in the quasi-elastic regime (confidence that an eruption is not imminent) and the unsteady inelastic regime (confidence that an eruption is imminent if VT rates are hyperbolic, or that it is not likely if the VT rates decay). The regime colours follow those in Fig. 1; the variations in (a) for steady VT event rate are incorporated into the increasing amount and range of uncertainty

The scheme assumes that the dykes forming before bulk failure do not reach the surface. This condition is most likely for eruptions from the summits of stable stratovolcanoes. It can break down, however, when the volcanoes erupt from their flanks or when their summits collapse (Fig. 5).

- *Flank eruptions.* Andesitic-dacitic volcanoes commonly have a vertical relief of 2.5 km or more (MacDonald 1972; Williams and

McBirney 1979). Dykes that would remain buried beneath the summit until bulk failure may thus be able to break the surface at an earlier stage if directed towards the volcano's lower flanks, either through a lateral breakout from a central dyke or from a dyke arriving from depth.

- *Flank collapse.* The shallow intrusion of dykes may trigger major collapse of a flank, exposing the magma and driving an eruption. A classic example is the 1980 eruption

of Mount St Helens in Washington State, USA (Mullineaux and Crandell 1981). For about two months after an emergency monitoring network had been deployed in late March, shallow intrusions created a surface bulge by as much as 147 m on the volcano's upper North flank (Moore and Albee 1981). The deformation was accompanied by phreatic explosions and a VT event rate that decreased from about 150 events per day in late March to an almost steady mean value of 25–35 events per day from late April to mid-May (for magnitudes larger than 2.5; Endo et al. (1981)). The unstable slope finally collapsed on 18 May, triggering a magmatic eruption sooner than expected (Mullineaux and Crandell 1981; Foxworthy and Hill 1982; Waitt 2014).

Flank collapse and the opening of flank vents may thus lead to magmatic eruptions before signs of bulk failure have developed, when a volcano is deforming inelastically but at a constant, and not a hyperbolically-increasing, rate of VT seismicity (Fig. 9). Supplementary evidence, such as ground deformation, might indicate potential flank activity or collapse but, as seen at Mount St Helens in 1980, cannot be relied upon for an unambiguous warning (Lipman et al. 1981; Voight 2000; Waitt 2014).

The levels in Fig. 9 provide a physical basis for connecting the potential for eruption to quantitative changes in VT seismicity and deformation, and to qualitative observations of surface phenomena. Immediate goals for testing the interpretation are (1) to simulate the growth of fracture networks around a magma body to determine the orientation of discontinuities at bulk failure, and (2) to quantify the dimensions of fractures and magma overpressures needed to propagate dykes during the early stages of inelastic deformation.

Further testing is also needed to evaluate how confidently precursory patterns can be recognised during a crisis. Thus, the underlying trends in Fig. 4 are apparent in hindsight when the complete sequence of unrest and its outcome are known. This is obviously not the case

during an emergency, when emerging trends have to be anticipated by extrapolating existing data. Uncertainty grows when fluctuations in VT event rate (1) obscure the nature of the underlying trend until it has continued for long enough to become firmly established (Kilburn 2003, 2018), and (2) introduce large time windows for estimating when changes in trend and the final rupture will occur (Bell et al. 2013, 2021; Boué et al. 2015; Vasseur et al. 2017). As a result of the long repose intervals, only a small number of field datasets are available for testing; however, by taking advantage of the scale-independent nature of elastic-brittle behaviour (Meredith et al. 1990; Main 1996), rock-physics experiments under simulated volcanic conditions (Burlini et al. 2007; Benson et al. 2008; Vasseur et al. 2017; Mordensky et al. 2019) offer the promise of new insights in quantifying the uncertainty on forecasts of elastic-brittle failure before eruption (Vasseur et al. 2017).

8 Self-regulating Behaviour and Similar Pre-eruptive Sequences

Similar behaviour patterns before eruptions are not inevitable. They demonstrate general similarities in the physical conditions beneath volcanoes while they prepare to erupt. Obvious similarities are the mechanical properties of the crust that resist fracture, the rheological properties of magma that resist flow, and the geometry of magma bodies that controls the shape of a deforming stress field. Less obvious is a preference to maintain steady rates of pressurization in a magma body, apparently a product of minimizing rates of energy dissipation during magma movement (Kilburn 2018).

The results from Soufriere Hills are consistent with two further natural constraints. First, magma chambers develop in crust with elevated pore-fluid pressures that may approach lithostatic values (Fig. 8) and, second, the shallowest level a magma body needs to reach before an eruption is when bulk failure creates a fracture that is large enough for a dyke to extend to

the surface (Figs. 6 and 7). The first condition allows tensile failure of the magma body, while the second explains the association between hyperbolic accelerations in VT seismicity and eruption.

The constraints favour similarity in the growth of shallow magmatic systems; similarity favours preferred patterns of pre-eruptive unrest; and preferred patterns raise confidence that deterministic forecasts of eruption are not only feasible, but can be made far enough ahead of time to be of practical value. Such optimism has been inherent in analyses of hyperbolic increases in VT event rate since they were first proposed by Voight (1988) as a general trend immediately before an eruption. Recognition that the hyperbolic sequences belong to a broader sequence of elastic-brittle failure with distinguishable stages (Kilburn 2018) opens the way to investigating whether, for example, the durations of previous stages (e.g., for exponential and steady VT event rates) can be used to anticipate the hyperbolic trend and so extend forecasts back to an earlier stage of unrest. A key message, then, is that individual classes of volcano (such as andesitic stratovolcanoes above subduction zones) can profitably be viewed as self-regulating systems that drive common patterns of unrest—not only to identify conditions in the crust that control how magmatic systems evolve, but also to anticipate their behaviour when unrest begins.

9 Conclusions

Andesitic-dacitic volcanoes show a restricted range of patterns of seismic unrest when they reawaken after long repose intervals. The patterns are illustrated by two historical episodes of unrest at Soufriere Hills volcano on Montserrat, one of which culminated in eruption. Their behaviour is consistent with the elastic-brittle deformation of crust above a pressurizing magma body several kilometres below ground.

Both episodes started with accelerating and then constant rates of VT seismicity as magma pressure increased the stress induced in the crust. The non-eruptive sequence closed with an Omori-style decay, for which the event rate declined inversely with time as the crust relaxed its stored stress while maintaining the same bulk strain (Fig. 4). The pre-eruptive sequence ended with a Voight-style acceleration, for which the event rate increased hyperbolically until bulk failure opened a major discontinuity that allowed magma to erupt and reduce the amount of pressurization (Fig. 4). In both cases, magma penetrated the edifice during the stage of steady VT seismicity.

The unrest can be explained by magma leaking from a pressure source until pressurization ceased or an eruption began. Conditions for tensile rupture indicate that crust near the magma body supported pore-fluid pressures at almost lithostatic values. The arrival of magma close to the surface before bulk failure suggests that the discontinuity forming during hyperbolic VT seismicity is not directed vertically, but instead grows laterally across the top of the pressure source (Fig. 6). Failure favours an eruption because the discontinuity is also large enough for a new dyke to reach the surface. Bulk failure thus defines the deepest level from which magma can erupt (Fig. 7). Once a pressure source has formed at this level, even shallower sources are not necessary because erupting magma relieves overpressure in the source body. High pore-fluid pressures and bulk failure together regulate the preferred depths of shallow magma bodies and the pre-eruptive behaviour of VT seismicity. These in turn favour similar patterns of unrest and, hence, opportunities not only to introduce deterministic constraints into previously probabilistic forecasts of eruption (Kilburn and Bell 2022), but also to explain to non-specialists why forecasts of eruption are still not perfect and, by raising understanding, stimulate co-operation in the design of operational alerts during an emergency (Fearnley et al. 2012; Kato and Yamasato 2013).

Acknowledgements I thank Ian Main and an anonymous reviewer for their help in clarifying the original version of the manuscript.

Appendix

How Stress Is Stored

Stress is typically described as the force per unit area applied to an object, such as the crust, and so is commonly treated as an external factor. Stress, though, is also a measure of internal state. The induced deformation changes the positions between atoms, increasing or decreasing the distance between them in tension or compression. The change in position requires a rearrangement of the internal energy within atoms. The classical picture of the atom divides internal energy into (1) the potential energy used to maintain an equilibrium spacing between atoms and (2) the kinetic energy used for vibrations about the equilibrium position (Azároff 1960; Young 1992). Deformation changes the proportion of internal energy used as potential energy. Hence stress also measures the change in potential energy within an atom, so that its units can be expressed as [Change in Potential Energy]/[Volume]. Stored stress thus describes the cumulative amount of the energy rearranged, and the stored differential stress the total difference in the amount used to change atomic spacing along the directions of maximum and minimum principal stress. When the crust relaxes completely, its atoms return to their equilibrium positions under lithostatic conditions, so restoring the starting division of internal energy between its potential and kinetic components.

Magma Ascent and Eruption

For the steady laminar flow of a Newtonian magma erupting through a dyke with a width W much wider than its thickness, or gape, X , an order-of-magnitude force balance gives [Force due to the pressure difference between the source

and the surface] – [Weight of magma in the dyke] = [Viscous resistance along the dyke], or

$$[(P_L + \Delta P)WX] - [\rho gLWX] \gg \mu(U/X) WL \quad (5)$$

where P_L and ΔP are the lithostatic pressure and source overpressure, ρ and μ are magma density and viscosity, U is the mean rate of ascent and L is the depth of the source.

Introducing the ascent time, $T = L/U$, Eq. (5) can be rearranged to give:

$$1/T \gg (\Delta P/\mu)(1 - \alpha)(X/L)^2 \quad (6)$$

where $\alpha = (P_L - \rho gL)/\Delta P$. (The equation is expressed in terms of $1/T$ rather than T to avoid the mathematical singularity of dividing by zero should $\alpha = 1$.)

At failure, the ratio of overpressure to tensile strength, $\Delta P/\sigma_T$ is $(\Delta P/S_d)(S_d/\sigma_T)$. $\Delta P/S_d$ depends on the geometry of the pressure source and is 1/2 for a vertical cylinder and 2/3 for a sphere (Saada 2009; Gudmundsson 2011). The 1995 VT sequence at Soufriere Hills gives $S_d/\sigma_T \approx 4$, from which $\Delta P/\sigma_T$ lies between 2 and 8/3. Hence, assigning σ_T a notional value of 10 MPa, ΔP lies in the range 20–30 MPa. The viscosity of Soufriere Hill's andesite has been estimated at 1–10 MPa s (Melnik and Sparks 2002).

Inserting the parameter estimates into Eq. (6) and setting $L = 6$ km and $X = 1$ –10 m (or $(L/X)^2 \sim 10^6$) for andesite dykes gives a range for the ascent time of $(10^6$ – $10^7)/(1 - \alpha)$ seconds. Petrologic data suggest ascent rates of $\sim 10^{-3}$ m s $^{-1}$ at the start of Soufriere Hills' eruption in 1995 (Devine et al. 1998). The rates yield ascent times of about 6×10^6 s, which are consistent with Eq. (6) for $\alpha \ll 1$, i.e., for a driving pressure dominated by the source overpressure, such that $T \approx (\mu/\Delta P)(L/X)^2$.

Differential Stress at the Margins of Pressurizing Bodies

The differential stress imposed by a pressurizing magma body is the difference between the effective compression acting perpendicular to

its surface and the tension acting around it. The effective compression in the crust is the magma pressure P_m minus the pore-fluid pressure P_p , while the tensile stress at failure is the tensile strength of the crust σ_T . Assuming that pressure in the crust is lithostatic (P_L) before magma pressurization begins, then the overpressure ΔP causing deformation is the difference between the magmatic and lithostatic pressures: $\Delta P = P_m - P_L$. Hence, when the crust fails around a magma body, the differential stress S_{F0} is $(P_m - P_p) - (-\sigma_T) = P_L + \Delta P - P_p + \sigma_T$. Dividing throughout by σ_T , this relation can be rearranged to give:

$$[1 - (\Delta P/S_{F0})](S_{F0}/\sigma_T) = 1 + (P_L/\sigma_T)[1 - (P_p/P_L)] \quad (7)$$

The ratio $\Delta P/S_{F0}$ depends on the geometry of the pressurizing body. $\Delta P/S_{F0} = 1/2$ for a cylinder and $2/3$ for a sphere (Saada 2009; Gudmundsson 2011). Hence we obtain for a cylinder

$$S_{F0}/\sigma_T = 2\{1 + (P_L/\sigma_T)[1 - (P_p/P_L)]\} \quad (8)$$

and for a sphere

$$S_{F0}/\sigma_T = 3\{1 + (P_L/\sigma_T)[1 - (P_p/P_L)]\} \quad (9)$$

which are the relations shown in Fig. 8.

Equation (8) applies to the circular wall of a cylinder, while Eq. (9) applies to the top of the sphere. Both assume that buoyancy effects across the depth of the magma body can be neglected. Methods for including buoyancy are described by Grosfils (2007).

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Machine Learning for Volcanology and Volcano Monitoring

Roberto Carniel and Silvina Raquel Guzmán

Abstract

Monitoring volcanic activity is crucial for ensuring the safety of nearby communities. An important step towards characterising volcanic regimes is the reduction of data into small, yet highly informative, feature vectors. Machine Learning (ML) has the potential to revolutionise volcano monitoring by efficiently processing large amounts of time series data, such as geophysical, geodetic, and geochemical observations, into feature vectors that can be analysed for similarities and differences, recognising patterns indicating unrest and potential precursors of specific eruptive phenomena, providing valuable insights that were previously not possible. However, sometimes ML tools can behave like “black boxes”, providing useful but hard to understand outputs. It is

therefore necessary to consider the interpretability of the results provided. This can lead to improved transparency, trust and reliability of the ML tools and in turn enhance decision-making. In this way, the application of sophisticated pattern recognition algorithms at different levels of abstraction, from classifying individual seismic events to recognising distinct levels of unrest and possible outcomes, can really enhance our understanding of volcanic activity and improve our ability to forecast what the volcano will do next.

1 Introduction

Volcanic eruptions can have significant economic and human impact, particularly when they occur near densely populated areas. The effects of ash falls, pyroclastic density currents, debris flows, and lahars can be devastating to communities, while lava flows can cause significant damage to infrastructure and property. Furthermore, active volcanoes often attract tourists, but they can also pose a significant threat to their safety (e.g., Etna, Italy in 1987; Yasur, Vanuatu in 1995; Kīlauea, Hawaii, USA in 2000; Stromboli, Italy in 2001 and 2019; Mayon, Philippines in 2013; Ontake, Japan in 2014; Brown et al. 2017; Whakaari, New Zealand in 2019; Dempsey et al. 2022 and most recently Marapi, Indonesia in 2023). It is crucial

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to understand the dynamics of these natural hazards and to develop effective monitoring and early warning systems to mitigate the volcanoes impact. The different Machine Learning (ML) techniques can help us in this task.

Forecasting volcanic eruptions can be challenging, as even stochastic forecasts—whose aim is to estimate the probability of given eruptive scenarios—are difficult, as noted by Jaquet and Carniel (2003) and Jaquet et al. (2006). Deterministic forecasts, which aim to predict when, where, and how an eruption will occur, are even more difficult. Despite this, volcano observatories often attempt to estimate the likelihood of the most dangerous volcanic events, as outlined by Aspinall et al. (2006). The monitoring of various data types can be used for forecasting, including e.g., seismic data (Ortiz et al. 2019), geomagnetic and electromagnetic data (Currenti et al. 2005), geochemical data (Green et al. 2013), deformation data (Ebmeier et al. 2019), infrasound data (Marchetti et al. 2019; Watson et al. 2022) and gas data (Aiuppa et al. 2010; Tamburello et al. 2013). When possible, an approach that can take into account data sources of different nature (Surono et al. 2012) is always advisable. This approach was followed e.g., for understanding near-surface processes in hydrothermal systems such as Dallol, Ethiopia (Carniel et al. 2010), Lipari, Aeolian Islands, Italy (Di Luccio et al. 2021), Kuchinoerabujima, Japan (Minami et al. 2022), or Whaakari, New Zealand (Caudron et al. 2021).

Seismology is a critical component of any monitoring system and must be based on the analysis of the full, continuous signal (Carniel 2014). Useful time series can then be built for the different volcano-seismic events: volcano-tectonic earthquakes (VT), rockfalls (RF), long-period (LP), very-long-period (VLP) and ultra-long period (ULP) events, and explosions. It is essential to consider these events separately as they are associated with different physical processes.

Manual classification and counting of such seismic events suffer from human subjectivity

and may become impossible during an unrest or seismic crisis (Cortés et al. 2019; Duque et al. 2021). For this reason, ML automated processing should replace manual classification. Of course, the same consideration also applies to the automated processing of other monitoring time series, such as infrasound, deformation, gas and water geochemistry, etc.

We may consider all monitoring time series (directly recorded or derived from original data) as observables of a complex dynamical system that can mathematically describe a volcano in a formal way (Carniel and Di Cecca 1999). With this approach, a state vector can describe at any time the state of the volcano, which moves along a trajectory in a state space. We can then monitor and detect with the help of ML the entrance into “unrest zones” of the state space and associate a probability of possible outcomes of the unrest.

ML is not limited to the processing of time series though. Photographs, ground-based and satellite-based images and videos, interferometric information from Synthetic Aperture Radar (SAR), thermal data from satellites (Marchese et al. 2006; Coppola et al. 2020), thermal data from the ground (Harris et al. 2005), and more in general remote sensing tools, can all benefit from the application of ML at different levels (Valade et al. 2019), from data cleaning and pre-processing (low-level) to data understanding and interpretation (high-level).

The application of ML is also not limited to monitoring a single active volcano; actually, ML has proven especially useful when analysing large data sets as is the case of dealing with multiple volcanoes. In fact, once they are setup, ML tools can process big amount of data in a very efficient way (e.g., Biggs et al. 2022). Other examples of application of ML include correlating generic stratigraphy (Janoušek et al. 2006), tephra units (Petrelli and Perugini 2016; Bolton et al. 2020) and ignimbrites (Brandmeier and Wörner 2016), a task that might be complicated to solve by the presence of deposits of similar age and similar geochemical and petrographic

features. ML is also effective in distinguishing tectonic settings from the geochemistry of volcanic rocks (Petrelli and Perugini 2016; Ueki et al. 2018). Recently it has also been used for the prediction of undetermined trace elements in volcanic rocks (Hong et al. 2019).

Although other review papers published in the recent past have partially collected applications somehow linked to ML and somehow related to volcanology (e.g., Carniel and Guzmán 2021; Ma and Mei 2021; Whitehead and Bebbington 2021; Matoza and Roman 2022; Thelen et al. 2022; Kilburn and Bell 2022; Andrews et al. 2022), the development and applications of ML methods to the study and monitoring of volcanoes is so rapid that it becomes very difficult to remain up-to-date and periodically new review papers are definitely needed. The increasing development of ML applications in volcanology and specifically in volcano monitoring is evidenced by the numerous contributions that appeared after the review by Carniel and Guzmán (2021) and that we discuss here.

2 What Is Machine Learning

2.1 Definitions

Machine Learning can be defined as a branch of computer science focused on the development of algorithms capable of *learning* from data without the need for explicit programming to make classifications, predictions or decisions. ML can also be defined as the study of algorithms that allow computer programs to improve automatically through experience (Mitchell 2006).

ML is just one of the ways we expect to achieve **Artificial Intelligence** (AI). The name AI has in fact a broader, more dynamic and fuzzy definition, e.g., B. A. Moore, former dean of the School of Computer Science at Carnegie Mellon University, defined it

as “the science and engineering of making computers behave in ways we thought until recently required human intelligence”. An **Artificial Neural Network** (ANN) is a specific computational model, designed to mimic the function and structure of the human brain, thus consisting of interconnected nodes (named neurons) arranged in parallel structures called layers. **Deep Learning** (DL) involves in turn the use of ANNs with many layers of neurons (in contrast to shallow ANNs that generally use very few layers). So, all these terms, which are often used improperly as synonymous, have in fact different meanings.

ML is somehow a generalisation of the idea of pattern recognition and is achieved by using a dataset of examples, which can be composed of natural, human-generated, or computer-generated data, to construct statistical models that can then generalise to new, unseen examples (Bishop 2007). In essence, ML is a methodology for problem-solving by creating models from existing data (Burkov 2019). ML is not limited to classification, but includes data mining, data reduction, synthetic data generation, and many more tasks and applications that are appearing almost every day. This review cannot therefore claim to be exhaustive. Python (Van Rossum and Drake 2009), R (R Core Team 2018), Java (Arnold et al. 2005), Javascript (Flanagan 2020), Julia (Bezanson et al. 2017; Jones et al. 2020) and Scala (Odersky et al. 2021) are among the most used computer languages for ML applications. Open access repositories hosted by e.g., GitHub (2024) offer a wide collection of libraries and examples of applications, also specifically in geophysics and volcanology. Although several (often open source) tools are mentioned below, providing a complete catalogue of all available ML tools is beyond the scope of this chapter.

A ML classification task is typically characterised by a series of steps: data reduction, model training, model validation, final deployment of the model to classify new, unknown data (see Fig. 1).

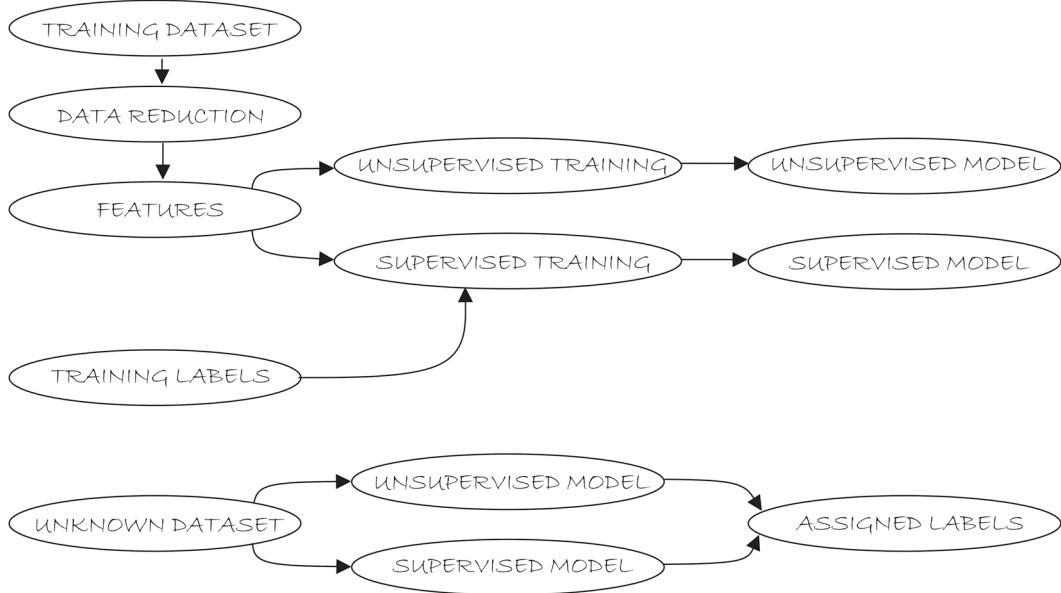


Fig. 1 Several steps are necessary to create and use a Machine Learning classification tool. Raw data (top) must first pass through a data reduction stage, which outputs information-rich feature vectors. These become

the training inputs for the models. The resulting models, after validation, are finally applied (bottom) to classify unknown data. Labels are needed for the training only in the (semi-)supervised approach

2.2 Data Reduction, Learning Strategies and Caveats

Training (that is, the actual learning phase) can be supervised, semi-supervised, unsupervised, or reinforcement based (Sarker 2021).

More training data does not necessarily mean better results. Indeed, low quality and irrelevant data can lead to poorer classification performance. Also, if we have many parameters for each data point (data vector), we may wonder how many of them are informative for our specific task. The dimensionality curse refers to the challenges that arise when dealing with high-dimensional data, particularly as the number of features/parameters/dimensions increases. The key issue is that as dimensionality grows, the volume of the feature space increases exponentially, making data sparse and increasing computational needs. In high-dimensional spaces it becomes more difficult to find patterns and making generalisations. Moreover, different ML

methods have different requirements in terms of the amount of data needed for an efficient training.

Several techniques can help us in this strongly needed process of **data reduction** (Ghojogh et al. 2023). If we start from raw data, we can consider data reduction as a sequence of feature extraction (compute data parameters), feature selection (choose the best ones) and feature reduction (optionally transform them into an optimal feature space), although these steps are often intermixed. One of the simplest data reduction concepts involves estimating parameters variance and assessing correlations between parameters. Each of the data vector's parameters that survive this stage becomes a potentially good feature and is intended to describe the data in a way that is complementary to the other features. The features should be as much independent and informative as possible, and most of all they should be able to help distinguishing the distinct categories we want to separate.

For example, if I need to describe an object, the colour is intuitively an interesting feature, but if I need to distinguish a mouse from an external hard disk and these are both black then the colour is not a useful feature to use.

Feature vectors do not need to be uniform. They can mix data of diverse types and exploit the possibilities given by the simultaneous use of multiparametric data from different sensors, although often this leads to additional problems of parameter normalisation. An important drawback however is that, if only one of the sensors used to build the feature vectors becomes unavailable, everything stops working, making the system far from being robust. This is probably why the applications of these ideas are not very widespread.

There are many dimensionality reduction algorithms (Cortés et al. 2016) where the output is a simplified feature vector that describes the data (almost) equally well. Independent Component Analysis (ICA) (Cabras et al. 2010), Non-negative Matrix Factorisation (NMF) (Carniel et al. 2014), Singular Value Decomposition (SVD) (Carniel et al. 2006), Principal Component Analysis (PCA) (Tharwat 2016) are all techniques aimed at finding a smaller number of independent features. Linear Discriminant Analysis (LDA) (Tharwat et al. 2017) uses the training samples to estimate the between-class and within-class variance matrices, and then uses Fisher's criterion to obtain the projection matrix for feature extraction (or feature reduction).

If a training dataset exists where each example feature vector has an accompanying label, a **supervised learning** approach can be applied. Each example feature vector is used as an input and the corresponding describing label is used as a desired output. In the case of discrete seismic events classification, these could be one of the types described before, i.e., VT, LP, VLP, ULP, Explosion, Rockfall, etc. The critical point in most of the cases is the reliability of these training labels, which is of the utmost importance: students cannot learn well from a teacher that shows wrong examples. In general, it is much better to have few events with reliable

labels than to have many more, but less reliable, labelled examples (Sarker 2021).

To decrease the time-consuming production of labels, sometimes active learning can be applied, i.e., a process by which another ML model chooses the optimum data for training (Settles 2009). Labels are then assigned by an expert only for these fewer training data.

If examples are available, but these are not labelled, one is forced to use an **unsupervised learning** training approach. The goal here is to recognise similarities between groups of feature vectors, and map all feature vectors to a value, a label or another vector that helps to understand the data and/or solve a specific problem. All the clustering algorithms fall into this category. In the unsupervised approach, in general the more examples can be used for the training, the better. Although data with a good Signal to Noise Ratio (SNR) is always better, also noisy data can often be used for the training. To optimize the choice of the most relevant features to use, several techniques of Unsupervised Feature Selection were proposed for unlabelled data (Solorio-Fernández et al. 2018).

Apart from supervised and unsupervised, there are other training approaches that stand somehow in the middle, namely the **semi-supervised learning** and the **transfer learning**. In the semi-supervised approach (Chapelle et al. 2006), the training is carried out using only a few labelled data (the supervised part) and many more unlabelled data (the unsupervised part). In the transfer learning approach (Pan and Yang 2010) we start from a model trained in another domain, even extremely far away from our application, but where abundant and reliable labelled data are available, and we refine it and adapt it to our target domain. The use of a pre-trained model can sometimes allow reaching satisfactory results even with very few labelled examples available in the target domain. A typical example is given by Large Language Models (LLM), which can be trained generically using huge quantity of texts in any domain, and then fine-tuned with few examples in the specific domain of interest. Volcanology seems an ideal case for this approach due to the common lack

of reliable labelled data for a classical supervised training, and examples of application can be found in the literature. Seismic data from Volcán de Fuego de Colima (Mexico) (Titos et al. 2020), Mount St. Helens (USA) and Bezymianny (Russia) (Bueno et al. 2020a) were analysed with this approach. Ardid et al. (2022) used similar precursory patterns seen in phreatic eruptions in Ruapehu, Tongariro, and Whakaari (New Zealand), Veniaminof and Pavlof (USA) and Bezymianny (Russia) to build a tool that could be applied to real-time monitoring at other volcanoes. Anantrasirichai et al. (2018) used a transfer learning approach to identify deformation in global datasets of Synthetic Aperture Radar (SAR) images.

Not always does the process of learning work smoothly if it is not carried out in a smart way. The stability-plasticity dilemma in ANN training refers to the balance between the ability to retain previous learning (stability) and the ability to adapt to new information (plasticity). The inability of neural networks to build knowledge incrementally over large periods of time is described as “catastrophic forgetting” (McCloskey and Cohen 1989). Previous learning is rapidly forgotten, because of an imbalance towards plasticity: neural networks tend to quickly unlearn old knowledge if it is not periodically shown again during the training. Finding the optimal balance between stability and plasticity is crucial for efficient incremental learning in neural networks. For instance, Riemer et al. (2019) proposed a method for **Continual Learning** (CL) with neural networks that can build incremental knowledge and avoid catastrophic forgetting, learning from non-stationary data streams. The non-stationarity is modelled by some schedule that determines how data are presented over time. However, if assumptions on this schedule are not met, unpredictable results can be produced. New CL methods have been recently proposed that are robust against arbitrary schedules over the same underlying data, as in real-world the schedules are in fact often unknown and dynamic (Wang et al. 2022).

A completely different learning approach is used by **Reinforcement Learning** (RL). Here

the model is described at a given time by a state (a feature vector) and can execute actions that result in gaining rewards or in getting penalties. In this case what the machine tries to learn, in a model-free or model-based adaptive way, is a behaviour, a policy or more generally a goal, based on incoming data and trial and error iterations, by seeking rewards rather than penalties. Typical RL applications are games (e.g., the AlphaGo model to play the Go game), logistics (to learn the most efficient way to order, store and distribute products), robotics (e.g. to learn complex movements or actions—this could be applied to robots to be used in volcano monitoring), autonomous driving (to learn how to take decisions in real-time), although not always free from threats (Lei et al. 2023). RL can also be applied to monitor the performance of ML models themselves to always guarantee acceptable quality. To our knowledge, this approach was proposed e.g., for industrial monitoring (Bhushan Gopaluni et al. 2020) but not yet for volcano monitoring.

Meta-Learning (MeL) is another approach that has been investigated by the recent ML literature to solve the high cost of training a specific model for each problem to be solved. MeL focuses on how to learn efficiently by leveraging existing knowledge and aims to find common representations that can be shared across multiple tasks. In particular, **Few-shot Learning** is a central problem in MeL, where models must quickly adapt to new tasks given limited training data (Wang et al. 2021).

ML is of course not perfect, and there are still **drawbacks and challenges** to be solved. Many times the output of ML tools are unexplained or difficult to interpret, and the tools often behave like “black boxes” that do not show the “reasoning behind” that leads to a given answer. This lack of **interpretability** can become a serious limitation. **Data quality and quantity** required for the training often becomes an issue, as also the possibility for models to generalise their application to volcanoes different from the one on which the training was carried out. Bias and systematic errors in the training can affect the results, and **computational requirements** may

also become an issue, especially for monitoring institutions in developing countries.

3 How Can We Apply Machine Learning?

ML can be applied to volcanology and volcano monitoring at very different levels. As we will see, it can be applied at a “high level” for solving specific volcanological and monitoring problems, but it can be also used at a “lower level”, e.g., in the data cleaning, preparation and preprocessing, thus facilitating the following, higher level tasks. In this section a selection of different ML methods will be introduced. Examples of the application of several of them will be then described in the next sections.

3.1 Cluster Analysis

Classification is one of the main applications in ML, and often this classification reduces to a binary choice: normal versus outlier, normal versus anomalous, correctly functioning versus failure, regular versus fraud transaction etc. (Caroline Cynthia and Thomas George 2021). This dichotomic classification can sometimes be applied also in volcanology e.g., separating quiet versus unrest phases (Manley et al. 2020).

In other occasions the problem can be described as the recognition of different classes/categories of data that share similar characteristics aimed at grouping them into clusters. Several methods of **Cluster Analysis** (CA) techniques were proposed with this purpose. Each of them measures similarity in a quantitative way using a suitably defined distance function between the different feature vectors representing the data. CA methods can be hierarchical, providing a tree-like structure that provides a hierarchy between the clusters, or non-hierarchical, where clusters are just grouping similar data according to an established distance (Fig. 2a). Hierarchical clustering can proceed in a “bottom-up” fashion (agglomerative), starting from one-member clusters with a single data point

and successively merging them while going up the hierarchy, or in a “top-down” way (divisive), where a single initial, all-including cluster is successively split into smaller clusters going down the hierarchy. In both cases, the hierarchy is finally presented in a graph which is called “dendrogram”. A vast class of algorithms can be found for carrying out a clusterisation.

K-means clustering is one of the most popular and aims to partition n data points into k clusters in which each observation belongs to the cluster with the nearest mean (cluster centre) that acts as cluster prototype. Better Euclidean solutions can be found using K-medians and K-medoids. K-medians use the median instead of the mean and minimise error over all clusters with respect to the 1-norm distance metric, as opposed to the squared 2-norm distance metric used by K-means. The K-medoids (Kaufman and Rousseeuw 1990) avoids the problem that in K-means the centre of a cluster is not necessarily a data point, as it is the mathematical average between the points in the cluster. The medoids used as centres are actual data points, which facilitates the interpretability of the meaning of such cluster centres.

Spectral clustering uses the spectral properties of a similarity graph derived from the data points to partition them into clusters. The aim is to find a low-dimensional embedding of the data points preserving their local structure. Donath and Hoffman (1973) first proposed using eigenvectors of the adjacency matrix for graph partitioning. The ratio cut method and the normalised cut methods followed, considering both inter-cluster and intra-cluster similarities. These methods efficiently capture the structure of complex data and can identify non-convex clusters (Ding et al. 2024).

Although the number of clusters must be usually fixed a priori, its determination is not straightforward. Several criteria can facilitate the optimal choice: The elbow method looks for an elbow of the graph of the explained variation as a function of the number of clusters, and/or its derivative (Kassambara 2017). The V-measure is an entropy-based external measure (Hirschberg and Rosenberg 2007) based on homogeneity

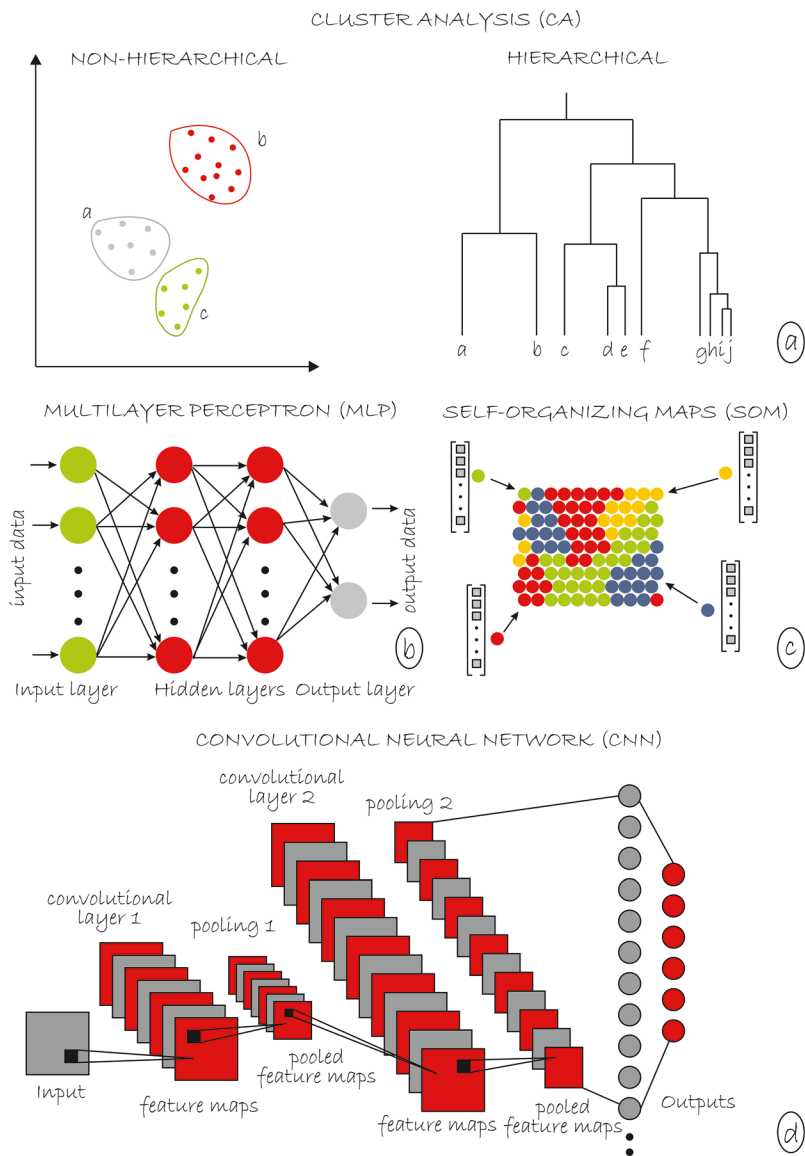


Fig. 2 **a** Cluster Analysis (CA) can be carried out with a hierarchical or non-hierarchical approach. **b** Multi Layer Perceptron (MLP) is one of the most common Artificial Neural Network (ANN) schemes. **c** Self-Organizing

Maps (SOM) look for auto-organisation of nearby nodes. **d** Convolutional Neural Networks (CNN) can use convolution on nodes input

and completeness criteria. The **Silhouette** method (Rousseeuw 1987) validates consistency within clusters of data. A side advantage of Silhouette analysis is that it can help to find the outliers present in a cluster. The **Davies–Bouldin** criterion (Davies and Bouldin 1979) examines the ratio between “within-cluster”

and “between-cluster” distances. As the likelihood always increases with the number of clusters, we have to trade off the “complexity of the model” against the likelihood (or “fit of the model”). The **Akaike Information Criterion** (AIC) (Akaike 1973) and the **Bayesian information criterion** (BIC) or Schwarz information

criterion (SIC, SBC, SBIC) (Schwarz 1978) are examples of this approach. The **gap statistic** criterion (Tibshirani et al. 2001) compares the total intra-cluster variation with their expected values under null reference distribution of the data. The optimal number of clusters will be the one that maximises the gap statistic. Many of the criteria described (and more) are available in the R package NbClust (Charrad et al. 2014). Unfortunately, often the number of clusters suggested by each of them is contradictory, making the final choice still not exactly straightforward.

The Density-Based Spatial Clustering of Applications with Noise (**DBSCAN**) sees clusters as dense regions in the data space, separated by regions of lower density of points, based on an intuitive subdivision of data into “clusters” and “noise” (Ester et al. 1996). The key idea is that for each point of a cluster, the neighbourhood of a given radius (R) has to contain at least a minimum number (M) of points. This approach can work better with clusters of irregular shapes and significantly contaminated by noise. Another advantage of the DBSCAN approach is that we don’t need to specify in advance the number of clusters. This is somehow substituted by the choice of the two mentioned parameters R and M . However, DBSCAN Clustering cannot efficiently handle high dimensional datasets and sparse datasets with varying density.

Other clustering variations are Mean-shift, Expectation–Maximisation (EM), Clustering using Gaussian Mixture Models (GMM), Agglomerative Hierarchical, Affinity Propagation, Spectral Clustering, Ward, Birch. Open-source implementations of most of these methods can be found in the Python library scikit-learn (Pedregosa et al. 2011).

3.2 Artificial Neural Networks

ANN is a generic name under which we can find a quite wide collection of algorithms. One of the most well-known is the **Multi-Layer Perceptron** (MLP), where nodes, i.e. “neurons”, are organised in several layers (Fig. 2b),

including an input layer directly connected to the input feature vectors, an output layer which provides the “solution” outside the network and, between those, one or more hidden layers (Fig. 2b). It has a feedforward architecture, i.e., information flows in one direction only, from the input layer through any hidden layers to the output layer.

The output of each node is filtered by a **non-linear activation function** that can help the ANN to learn and model complex, nonlinear relationships in the data and/or “mute” completely the output to suppress irrelevant information and increase sparsity in the ANN. Common nonlinear activation functions include sigmoid (logistic), tanh, ReLU (Rectified Linear Unit), GELU (Gaussian Error Linear Unit).

The training of MLPs consists in the tuning of the weights of the “**dendrites**” connecting the nodes and is carried out through a **backpropagation** mechanism. The application of MLPs to volcano-seismic data was proposed e.g., for Stromboli by Carniel (1996) and for Vesuvius by Scarpetta et al. (2005) and Esposito et al. (2013). **Extreme Learning Machine** (ELM) is an improved feedforward neural network, usually with a single randomised hidden layer, with better generalisation performance on simple tasks only and much faster learning speed, typically in a single step (Huang et al. 2012). ELM can be combined with other algorithms, such as an Improved Sparrow Search Algorithm (ISSA) to get better performance for specific tasks, e.g., prediction (Li and Wu 2022).

Kohonen maps, better known as **Self Organizing Maps** (SOM) (Kohonen 1982, 2001) are another approach to the problem of unsupervised classification (Fig. 2c). SOM are a specific type of ANNs, aimed to produce a low dimensional (e.g., 2D) map which represents the feature space in a more compact way. A combination of competition and collaboration between the nodes of the SOM is at the base of the training, grouping similar inputs using a neighbourhood function that preserves their topological properties of “closeness”. SOM were applied several times to the classification of volcano-seismic data and especially to volcanic

tremor regimes (Köhler et al. 2010; Carniel et al. 2013a, b; Di Luccio et al. 2021; Giudicepietro et al. 2021).

Shallow Neural Networks (the classical ANN) usually include only 1 or 2 hidden layers, while **Deep Neural Networks** (DNN) significantly increase the number of hidden layers (and consequently of neurons) to obtain higher level functions from the inputs, transforming the data into more flexible and abstract representations. DNNs can be used both with a supervised and with an unsupervised approach. The deep representation learning process in DNNs involves progressively extracting and transforming features from raw data, enabling the network to capture intricate patterns within the data and learn increasingly abstract and complex representations. However, it is always important to remember that more nodes and more connections also imply more parameters to be tuned, and in turn a longer and more difficult training phase (Koutsoukas et al. 2017).

Traditional clustering tools lose efficiency in presence of increasingly high dimensional data. In order to use DNN for clustering, the straightforward way is to first learn the deep representation of the data, and then feed it into a classical clustering method. Doing this however does not produce a deep representation optimised for clustering, although the optimisations of the clustering and representation learning are dependent on each other. The concept of **Deep Clustering** was therefore proposed to jointly optimise the representation learning and the clustering (Sigadapu et al. 2023).

Convolutional Neural Networks (CNN) (Fig. 2d) belong to the DNN class and were specifically designed for processing and analysing visual data. CNN consist of multiple layers, including the input layer, at least a convolutional layer, a pooling layer, other fully connected layers and normalising layers (Titos et al. 2020). The convolutional layers convolve their inputs with a multiplication or other dot product to extract features from input images, while the pooling layer downsamples the data to reduce computation time and improve efficiency. Through backpropagation and gradient descent,

CNN learn optimal filters to identify patterns within images. CNN nowadays typically use a rectified linear unit (ReLU) as the activation function, together with pooling layers, fully connected layers and normalizing layers. One key aspect of CNN is their ability to automatically learn and build hierarchical representations of features at different levels of abstraction from raw data without the need for manual feature extraction (e.g., edges detection). This provides a scalable approach to image classification and object recognition and allows CNN to identify complex patterns and structures within images, making them highly effective in complex tasks where other methods fail. Typical applications are image recognition systems, autonomous vehicles, medical and satellite images analysis, but they can be used also for analysing time series like seismic or other geophysical data. CNN have been applied in volcanology for e.g. the detection of volcanic ash plumes in camera images (Guerrero Tello et al. 2022), the classification of volcanic seismic signals layers (Titos et al. 2020) and the detection of volcanic deformation (Anantrasirichai et al. 2018).

A **Recurrent Neural Network** (RNN) (Titos et al. 2019) is an ANN where neuron outputs can be used as inputs for other neurons in the same layer, creating a feedback loop (Fig. 3a) where information is retained during the training. RNNs have the unique ability to retain memory of past inputs through hidden states, allowing them to capture dependencies in sequential data and are therefore a natural candidate to process time series data and solve tasks where past inputs influence current predictions. A subset of RNNs, named **Long Short Term Memory networks** (LSTM) and available both in the supervised and unsupervised versions, can retain information for extended periods of time and therefore learn long-term dependencies (Hochreiter and Schmidhuber 1997). **Gated Recurrent Units** (GRU) handle long-term dependencies by updating and forgetting gates to selectively retain or discard information in memory. GRU lacks a context vector or output gate, resulting in fewer parameters than LSTM. Although these methods are potentially more

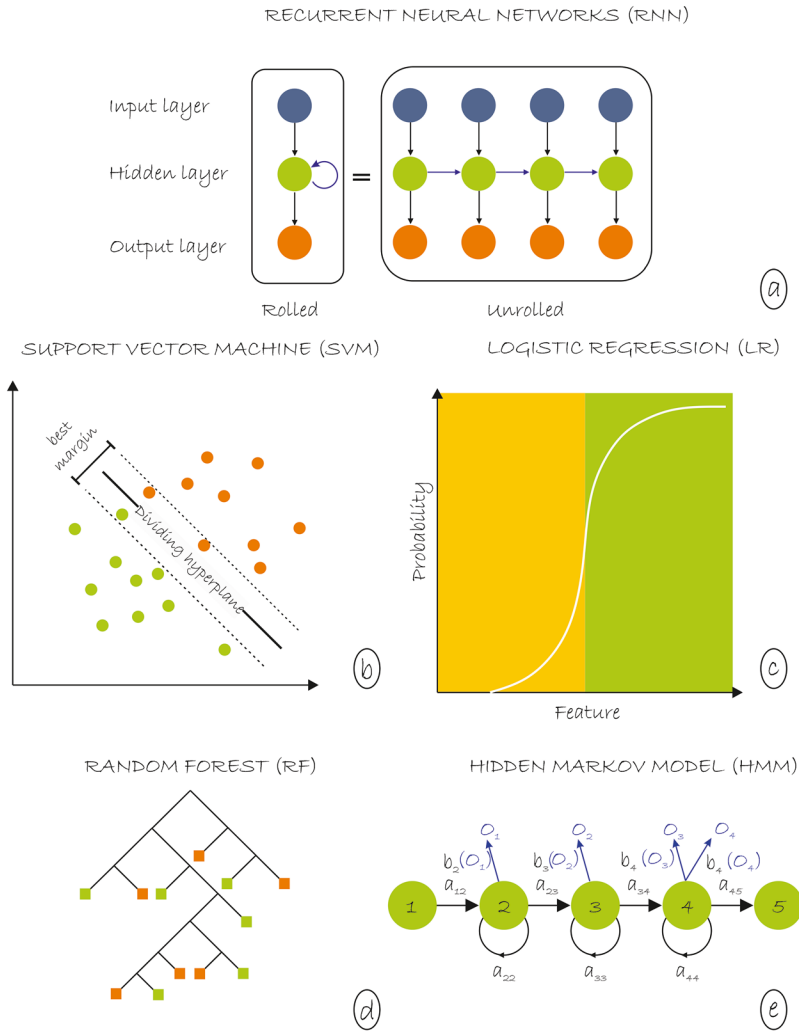


Fig. 3 **a** Recurrent Neural Networks (RNN) introduce a feedback mechanism in the Artificial Neural Networks (ANN) scheme. **b** Support Vector Machines (SVM) look for an optimal gap to separate different categories. **c** Logistic Regression (LR) uses linear dependences on the

features. **d** Random Forests (RF) use a concept similar to bagging to minimise correlation between its trees. **e** Hidden Markov Models (HMM) are a statistical scheme that maximise data time dependence

powerful than classical ‘memory-free’ ANNs, the ‘memory-loop’ noticeably increases their training time. RNNs have rarely been used in volcanology e.g. for seismic events classification (Titos et al. 2019).

Another approach that has recently emerged is **Physics-Informed Neural Networks** (PINNs), the integration of traditional physics-based modelling with ML techniques. Several

classes of methodologies used to construct physics-guided ML models and hybrid physics-ML frameworks were proposed with names like “physics-guided ML,” “physics-informed ML,” or “physics-aware AI” and more generally interpreted as “scientific knowledge-guided AI” (Willard et al. 2022). One of the few examples of application in volcanology is the use of time-dependent scattering, physics informed through

data time–frequency representation, for volcano eruption forecasting (Bueno Rodríguez et al. 2022).

3.3 Other ML Approaches

Support Vector Machines (SVM) (Fig. 3b) are a supervised statistical learning framework often used as a non-probabilistic binary classifier (Cortés and Vapnik 1995; Masotti et al. 2006). Categories are separated by seeking an optimal hyperplane that maximises the gap between different classes of training data points. This hyperplane acts then as a decision boundary, separating new data points into the distinct categories according to the side of the gap where they are located. A key concept is to transform input data into a higher-dimensional feature space, where it is easier to find a linear separation even for complex datasets that cannot be separated by a simple straight line in the original space. SVMs employ kernel functions for this transformation. With these kernel functions (linear kernels, polynomial kernels, radial basis function—RBF kernels, sigmoid kernels) SVMs can efficiently classify non-linearly separable data by mapping them into a space with a linear decision boundary. SVMs can implicitly compute efficient dot products between transformed feature vectors, and show often particularly good performance in cases where limited training samples are available.

In the supervised **Logistic Regression (LR)** models (Fig. 3c) (McCullagh and Nelder 1989) we have a linear dependence of the classification probability on the features. To reduce the number of dimensions of the input feature vectors, we can apply techniques such as the **Least Absolute Shrinkage and Selection Operator (LASSO)** (Hastie et al. 2009).

The supervised **Sparse Multinomial Logistic Regression (SMLR)** models classify by incorporating weighted sums of basis functions where weight estimates are encouraged to be either significantly large or exactly zero (Krishnapuram et al. 2005). The use of sparsity

is somehow exploited in a similar way to **Non-negative Matrix Factorisation (NMF)** (Cabras et al. 2012). SMLR can include automatic feature selection, minimisation of the number of used basis functions and can easily scale up in both the number of samples and the dimension of the feature vectors.

In a **Decision Tree (DT)**, features are examined one at a time at each node of the tree, and on the base of their value one or the other of two branches is followed until a leaf node is reached, corresponding to the assignment to a given class. While it is common for DT to split into exactly two branches at each node, this is not a strict rule. DT can branch into more than two paths, especially when dealing with multiple features or complex decision-making processes. Different supervised strategies can be applied in this class of models, giving birth to methods such as Functional Tree (FT), Best First Decision Tree (BFT), J48 Decision Tree (J48DT), Naïve Bayes Tree (NBT) and Reduced Error Pruning Trees (REPT). One can also combine the output of different trees using ensemble learning techniques such as Random SubSpace (RSS) (Pham et al. 2020).

Boosting is a type of ensemble meta-algorithm commonly (but not exclusively) associated with supervised learning. The idea is to use the training data to create multiple models, in an iterative manner, using a weak learner. Each model would be distinct from the previous one as the weak learners attempt to “correct” the mistakes made by previous models. An ensemble model will finally combine the results of the various weak models (Mienye and Sun 2022).

Bootstrap aggregation, or simply **Bagging**, is a similar approach, which starts by creating many “almost-copies” of the training data, with each copy slightly different from the others. A weak learner is applied to each copy and the results are finally combined. The **Random Forest (RF)** (Breiman 2001) implements the bagging concept with the peculiarity that a random subset of the features is chosen at each learning step. This helps to minimise correlation between the trees, which increases the

classification accuracy. It is critical to pay close attention to the number of trees and the size of the random feature subsets.

The assumption that a Markov process is generating the data under study is at the base of the **Hidden Markov Models** (HMM). These models describe an event as a sequence of states, where the probability of entering a given state only depends on the previous one. A combination of HMM can describe a sequence of events. Although the states are not directly observable (hence the name “hidden”), a “message” is produced by the model at the end of each transition, and its value depends probabilistically on the reached state. This formulation easily exploits any time dependence in the data and was therefore applied e.g., to volcano seismology (Alasonati et al. 2006; Beyreuther et al. 2008; Ibáñez et al. 2009; Beyreuther and Wassermann 2011).

3.4 Generative Algorithms

Generative algorithms (GA) in AI, also known as **Generative Artificial Intelligence** (GAI) (Gupta et al. 2024), often belong to the category of DL (they are then called Deep Generative Models) and have the capacity to generate content from a prompt or input, learning patterns and structures from the training data and producing new data that aligns with these learned patterns (Bond-Taylor et al. 2022). Content is sufficiently generic to include text, images, audio, video and synthetic data. GA comprehend a range of approaches that, often starting from the ideas at the base of the classical autoregressive models, evolved in different directions.

Normalizing Flows (NF) transform a simple distribution into a complex distribution through a series of invertible transformations. By chaining several of these transformations, NF can capture rich dependencies in the data, providing exact likelihood estimations, enabling accurate modelling of data distributions and efficient inference (Papamakarios et al. 2021).

Generative Adversarial Networks (GAN) consist of two neural networks—a generator and a discriminator—engaged in a zero-sum game where the generator creates synthetic data to deceive the discriminator, which aims to distinguish between real and fake data. This adversarial setup leads to the generation of content more and more compatible to the training data, thus more and more realistic (Gui et al. 2020).

Variational AutoEncoders (VAE) encode data into a latent space and then decode it back to reconstruct the original data. VAE learn in this way probabilistic representations of input data, enabling them to generate new samples from learnt distributions. These models focus on encoding data efficiently and regenerating it accurately, making them also valuable for tasks like image generation, anomaly detection but also various classification and compression (Kingma and Welling 2019). Auto-encoders can be also used to find a smaller number of independent features (Guo et al. 2020).

Generative Pre-trained Transformers (GPT) represent a class of models that have recently become well known even to the general public thanks to their language processing and understanding capabilities, that allow them to produce contextually relevant text. They use attention mechanisms to model the relationships between different elements effectively in a sequence. GPT can become so efficient **Large Language Models** (LLM) for natural language processing tasks that sometimes differentiating between human and AI authorship becomes challenging. However, although LLM is somehow the “killer application”, there are many other possible uses of GPT: medical research, drug development, cyber security, data augmentation, generation of synthetic data for research, data analysis, industrial automation. Sufi (2024) compares more than 50 research publications, evaluating research domains, methodologies, advantages and disadvantages of GPT focusing in particular on Data Augmentation.

Each approach to generative algorithms has many variations and implementations on a

common starting idea. However, the approaches are usually not mutually exclusive and can be combined to produce hybrid methods.

4 Applications to Seismic and Infrasonic Data

There is usually some change in seismic activity prior to an eruption, making seismic data one of the key datasets in any attempt to forecast the future volcanic activity (Ortiz et al. 2019), especially if combined with other data in a multi-parametric approach (Caudron et al. 2021). One can apply statistical/Bayesian methods to automatically determine significant changepoints in the time series of the number of detected seismic events (Sholihat et al. 2021) or any other more sophisticated parameter derived from seismic data (Carniel and Tárraga 2006). Bueno Rodríguez et al. (2022) studied the significance of these changepoints for forecasting eruptions at Bezymianny and Etna in combination with deep convolutional LSTM.

4.1 Seismic Events Classification

Within the continuous seismic stream, different seismic events give us information about different physical processes in the volcano. VT events can be described as “classical” earthquakes that occur in a volcanic environment and may indicate magma movement (McNutt 2002; Zobin 2016). Explosion earthquakes are generated by sudden extrusion of magma, ash and gas in a blast event, often associated with VLP events (Marchetti and Ripepe 2005). LP events have great potential for forecasting (Chouet 2003), although this can be influenced by their controversial interpretation, which can involve fluid-driven flow (Julian 1994), eddy shedding, turbulent slug flow, soda bottle analogues (Hellweg 2000), the repeated expansion and compression of subhorizontal cracks filled with steam or other ash-laden gas (Molina et al. 2004), seismic energy trapped after a magma rupture in a brittle manner (Neuberg et al.

2006), stick-slip magma motion (Iverson 2008), deformation acceleration of solidified domes (Johnson et al. 2008), and slow ruptures (Bean et al. 2014). It is clear that the interpretation of the automatically classified and counted LPs will depend on the underlying chosen LP generation model.

“Tremor episodes” (TRE events) are also described and counted in many works, mostly in connection with magma degassing (McNutt 2002). However, a volcano with any activity produces a continuous tremor, the detectability of which depends only on the sensitivity of the seismic instruments (Carniel 2010; Jolly et al. 2020). Therefore, the TRE class should be better defined as a “tremor episode that exceeds the detection limits”. Continuous tremor is more valuable (Tárraga et al. 2014) due to its persistence and memory, i.e., the ability to retain information from a given amount of time in the past, which can in turn help to forecast its future behaviour (Jaquet and Carniel 2003; Jaquet et al. 2006). Tremor is also sensitive to external triggers such as regional tectonic events (Carniel and Tárraga 2006), earth tides (Dumont et al. 2020), and lunar cycles (Girona et al. 2018). Additionally, changes in tremor over time can indicate variations in other parameters such as gas flow (Julian 1994). Spectral, dynamical, stochastic parameters can all be used for monitoring and successive ML classification (Carniel 2014).

Two paroxysmal eruptions observed at Stromboli in 2019 were the test study used by Romano et al. (2022) to conceive and test an early-warning algorithm based on SOM and cross-correlation, using data from a Sacks-Evertson strainmeter instead of the classical seismometer. The classification allowed the authors to establish a link between VLP and ULP shape variation forms and volcanic activity, reaching warning anticipation of days instead of minutes. Their innovative analysis of dynamic strain may be used to provide an early-warning system also on other open conduit active volcanoes.

Of course, at volcanoes we can also see natural but non-volcanic seismic signals like distant

tectonic earthquakes, distant explosions etc., together with anthropogenic signals produced e.g., by industry, ground vehicles, helicopters used for surveillance, etc. These uninteresting events can sometimes be grouped into a generic “garbage” category.

4.2 Monitoring and Forecasting Volcanic Activity

As mentioned in the introduction, manually detecting and classifying discrete events can be very time consuming, up to becoming impossible during a volcanic crisis. Therefore, ML classification procedures are also very valuable as a first step towards more classical forecasting methods such as material **Failure Forecast Method** (FFM) (Tárraga et al. 2008). FFM is based on the recognition of an acceleration pattern of a given parameter. For the seismicity, the parameter is usually either the rate of occurrence of seismic events or some estimate of energy of the continuous seismic signal (e.g., RSAM or RSEM). In both cases, improvements can be obtained combining FFM with ML by examining separately each class of seismic events, again because they may have very different origin and thus reflect different physical processes on which we would like to focus (Boué et al. 2015). In a similar way, assuming the existence of a correlation between (some) seismic signals and lava lake level fluctuations, Burgi et al. (2020) used the elevation of the lava lake of Nyiragongo (Democratic Republic of Congo) as the accelerating parameter for the FFM.

4.3 Data Reduction: The Choice of Relevant Features

Feature vectors for seismic data should be chosen to maximise the information about the source we want to monitor, while minimising path and site effects. In many cases, they do not need to be linked to the specific physical model that describes the phenomenon, therefore allowing ML to be applied even in the absence of a

scientific consensus on the generation mechanisms of a particular seismic signal, e.g., a LP event. The application of some kind of standardisation procedure can improve the results and is therefore usually advisable (Cortés et al. 2019). Feature vectors can include a heterogeneous mix of parameters coming from time and frequency domains, correlations, statistics, dynamical analysis, and any other data reduction techniques (Carniel 2014). Malfante et al. (2018b) divides features into “Statistical features”, “Entropy features”, and “Shape descriptors”, and in turn into “Time domain”, “Spectral domain” and “Cepstral domain”. Many examples can be found in the literature, including linear predictor coding of spectrograms (Scarpetta et al. 2005), spectral autocorrelation functions (Langer et al. 2006), statistical and cepstrum coefficients (Ibáñez et al. 2009) and wavelet transforms (Jones et al. 2012). The extracted feature vector can become the input to any of the ML methods.

Copahue volcano (Argentina–Chile border) started a new eruptive cycle in July 2012 with several phreato-magmatic and strombolian explosions (Petrinovic et al. 2014). Different methodologies were proposed to build efficient feature vectors to analyse the same continuous seismic data, highlighting the importance of data reduction. Melchor et al. (2020) used permutation entropy and polarisation degree among others to characterise long-duration volcanic tremor. Hantusch et al. (2021) tracked variations of parameters linked to seismic noise energy to look for precursors of eruptive phases. Melchor et al. (2022a) used spectral content, polarisation degree, rectilinearity, horizontal azimuth and vertical incidence and proposed two coefficients CP and CL for describing to what extent the wavefield is polarised. The time variations of these parameters are then correlated to the level of the crater lake, deformation, temperature, and explosive activity. Finally, Melchor et al. (2022b) proposed the extraction of dominant peaks (relative maximum in successive PSD) and dominant frequencies (i.e., relative maximums in the PDF of dominant peaks). The time evolution of dominant peaks and their polarisation attributes allows to identify different tremor

sources. These papers show how even slight variations on the same processing ideas can provide different information and results. The smart selection of convenient features to describe the data can increase significantly the effectiveness of the ML techniques.

4.4 Applications of Clustering

CA is probably the most used class of all unsupervised techniques, and the applications to volcano seismology follow this general rule. Clustering LPs into families allows to identify events with similar location and similar source processes. This implies the existence of a highly repeatable source (Neuberg et al. 2006). If we normalise the data before clustering, we give more importance to shape with respect to size of the events. In this case we assume a repeatable source that is also scalable; examples include Soufrière Hills Volcano, Montserrat, UK (Green and Neuberg 2006) and Irazú volcano, Costa Rica (Villegas et al. 2022). Kanlaon volcano (Philippines) is another example where classes of events resulting from the clustering were then used to stack, detect additional events, and obtain more accurate phase arrivals (Sevilla et al. 2020). Repeating Earthquake Detector in Python (REDPy) is an efficient open-source package than can be used to apply this procedure to other data (Hotovec-Ellis and Jeffries 2023). REDPy was used by Wellik et al. (2021) to classify the seismicity linked to the 2017 eruption of Mt. Agung in Bali, Indonesia. The resulting event families show that Agung was approaching an eruption notwithstanding decreasing earthquake rates and RSAM values. This example suggests how eruption forecasts can be improved by this kind of tools for the study of repeating earthquakes.

Ren et al. (2020) applied spectral clustering (using connectivity rather than compactness for clustering) to investigate recurring patterns in 6 years of continuous seismic data from the Piton de la Fournaise volcano (La Réunion

island, France) during quiet periods and during eruptions. Duque et al. (2020) applied six different unsupervised, clustering-based methods to classify volcano seismic events recorded at Cotopaxi Volcano (Ecuador).

4.5 Applications of Artificial Neural Networks

ANN, mostly in their prototypical form of MLP, were applied to seismic data recorded at several volcanoes, including Stromboli, Italy (Falsaperla et al. 1996; Carniel 1996), Etna, Italy (Langer et al. 2009) and Vesuvius, Italy (Scarpetta et al. 2005). An analysis of Villarrica (Chile) seismic data was carried out using genetic algorithms in order to optimise the MLP configuration (Curilem et al. 2009), while more sophisticated DNN architectures were applied e.g., to Volcán de Fuego, Colima, Mexico (Titos et al. 2018). Llaima volcano (Chile) seismic data were classified by CNN, with results compared to other methods of classification (Canário et al. 2020). Signals of Deception Island Volcano in Antarctica were classified by different methods, including RNNs (Titos et al. 2019). These last architectures showed good generalisation accuracy: models trained on 1995 and 2002 data were able to classify with satisfactory results 2016–2017 data. MLP and other architectures were used by Konstantinou et al. (2022) in combination with Permutation Entropy to detect emerging “tremor episodes” and lahar events at Redoubt, Alaska, USA.

DNN with transfer learning were used by Lapins et al. (2021) for automatic P and S detection at Nabro volcano (Eritrea), but the detection system must be trained with labelled data at the specific volcano. Castilla et al. (2023) proposed instead an algorithm, developed on the Nevados de Chillán Volcanic Complex (Chile), where specific seismic features are extracted mainly from the spectrogram that can be used without labels and can therefore be more easily used at another volcano, although some parameters

must be still fine-tuned. The automatic detection of phases, and in turn the localisation of events, can be very important during a volcanic crisis when the seismic activity becomes very intense. PhaseNet, a method based on DNN used with Earthworm and SeisComP3 (i.e., softwares used for real-time seismological data acquisition, processing, and analysis), is now used routinely to monitor seismicity in Mayotte and Martinique, France (Retailleau et al. 2022).

Good generalisation capabilities were achieved using SOM, popular in volcano-seismology with different geometrical variations (rectangular vs. hexagonal nearest neighbours cells; planar vs. toroidal vs. spherical maps); they were applied e.g., to Raoul Island in New Zealand (Carniel et al. 2013a). SOM results on volcanic tremor can be then post-processed via a hierarchical clustering; this was carried out e.g., in the Scilab environment (Scilab 2023) at Ruapehu (Carniel et al. 2013b) and at Tongariro (Jolly et al. 2014) in New Zealand and in the Matlab environment (Matlab 2023) at Etna, Italy (Messina and Langer 2011). SOM were also used by Giudicepietro et al. (2021) to investigate the degassing processes of volcanic systems through seismo-acoustic signals generated by analogue laboratory experiments. SOM's ability to cluster experimental events under different controlled conditions was tested using different analogue magma viscosity, gas flux, and conduit roughness. The capacity of SOMs to classify infrasonic data caused by shallow Strombolian explosions or degassing in a real volcano monitoring system was recently confirmed at Etna by Eckel et al. (2023). The SOM approach in this case follows previous attempts at Etna using unsupervised K-means CA using time and frequency domain features (Watson 2020). Recently, SOM has been applied, together with K-means and Kernel Density Estimation, to the identification of volcanic tremor regimes at Whaakari (New Zealand), with an innovative focus on the statistics-based optimisation of the chosen SOM hyperparameters (Steinke et al. 2023).

4.6 Applications of Other ML Methods, Opportunities and Limitations

The difficulties of generalisation of models, even if trained on the same volcano, was highlighted e.g. at Piton de la Fournaise (La Réunion island, France), comparing data from 2009–2011 and 2014–2015 (Hibert et al. 2017). The study used RF to classify rockfalls and VT. Although excellent results were obtained by the model (using a set of 60 features, trained on 2009–2011 dataset), applying it to new data recorded in 2014–2015 (unseen during the training phase) did not provide satisfactory results (Hibert et al. 2017). At Whakaari (New Zealand) RF were instead used to derive ensemble mean decision tree predictions of sudden steam-driven eruptions (Dempsey et al. 2020). A critical evaluation of the performances of probabilistic eruption forecasting at Whaakari was successively published by Dempsey et al. (2022).

Passive seismic interferometry examines the relative stability of seismic sources using the time evolution of cross-correlation functions. Yates et al. (2023) applied agglomerative hierarchical clustering to cross-correlation functions at Piton de la Fournaise (La Réunion Island, France) and Ruapehu (New Zealand) without using a defined reference period. Changes are recognised both in the source of volcanic tremor and in the medium due to magma intrusions. Care must be taken, however, not to misinterpret changes due to instrumental problems. It is also interesting that similarity patterns show that Ruapehu tremor can be sometimes seen as a repeatable seismic source.

Volcanic seismic signals recorded at Llaima, Chile (Curilem et al. 2016) and Ubinas, Peru (Malfante et al. 2018a) are among the examples of application of SVM. Earthquake predictions in Indonesia, with a focus on volcanoes, were attempted by Multinomial Logistic Regression after a training based on 30 years of data (Murwantara et al. 2020).

When classifying volcano seismic data, accuracy is not the only criterion to be used in evaluation. Many accurate methods represent in fact “black boxes” that do not provide clear interpretation of the results. According to Karpatne et al. (2018), interpretability is a fundamental goal in geosciences, as it increases the confidence of the experts in automatic systems, allowing them to understand the reasons behind classifier outcomes, obtain additional knowledge and better understand the classification errors (Bicego et al. 2015) in an increasingly transparent manner. Talebi et al. (2020) lists interpretability among the five minimum criteria required for ML methods applied to geosciences (the others are transparency, accuracy, credibility, and physical realism).

Some approaches, such as SVM and RF, allow for easier interpretation of results at various levels, as they are relatively transparent compared to more complex algorithms like (deep) neural networks. SVM decisions are influenced by support vectors, making it easy to see which data points are critical for classification. RF consist of decision trees that follow clear if–then rules, so one can analyse feature importance or examine individual trees to understand how decisions are made. Compared to “black-box” models like deep neural networks, these models provide therefore clearer insight into why a particular decision was made.

Regarding the seismic hazard of volcanic activity, one or more subsequent large earthquakes (SLE) of magnitudes similar or larger can follow an initial energetic quake. Gentili and Di Giovambattista (2017) proposed a DT-based approach, improved by Gentili and Di Giovambattista (2020) who proposed the algorithm NESTORE (Next STRong Related Earthquake). NESTORE was applied to different areas of the world, optimizing the choice of the features used on each specific area with different seismicity characteristics and catalog quality. The latest version of the method (NESTORE_M2) was applied to California seismicity (Gentili and Di Giovambattista 2022) together with a more robust approach, rNESTORE, to reduce overfitting problems. Most of the relevant

literature deals with non-volcanic earthquakes; nevertheless, similar ideas can be applied to the volcanic case.

Distinct phases of detection and subsequent classification are a common approach to the recognition of discrete seismic events. In other words, the classification is applied to events that were already extracted from the continuous seismic data (Malfante et al. 2018a). To decrease the time requested for labelling in the supervised approach, the choice of which data to label can be supported by active learning models, as proposed by Manley et al. (2022) for the training of a CNN for Nevado del Ruiz (Colombia) and Llaima (Chile).

The approach of a continuous HMM goes a different way, i.e., it aims at labelling in a single step the different parts of a continuous stream, also in real-time. The efficient use of time “direction” is of the utmost importance to distinguish different types of seismic events in the continuous stream, e.g., S waves can only follow the P phase. Benítez et al. (2007), Dawson et al. (2010), Bicego et al. (2013), Boué et al. (2015), Trujillo-Castrillón et al. (2018) are among the many authors that followed this powerful approach. Colima and Popocatepetl in Mexico are routinely monitored using HMM (Cortés et al. 2009). Cortés et al. (2019) proposed to combine HMM with Empirical Mode Decomposition, improving noisy events classification and providing another step toward a volcano independent unsupervised paradigm.

At Etna (Italy), a quite different problem was tackled by using HMM. Here, seismic data from multiple stations during a period of lava fountaining are mapped into symbols of an alphabet with the Symbolic Aggregate approXimation (SAX, Lin et al. 2007) before being processed by a HMM to obtain an automatic recognition of the different states of volcanic activity (Quiet, Pre-Fountain, Fountain, Post-Fountain) for monitoring purposes (Cassisi et al. 2016).

RF were used in multi-seismic-station approach at Piton de la Fournaise, La Réunion island, France (Maggi et al. 2017; Ren et al. 2020). EMD, SVM and Principal Components were at the base of the multi-station classifier

proposed at Ubinas volcano in Peru (Lara et al. 2020).

Another critical issue is the amount of available training data. To train a supervised model to accurately classify seismic events, it is important to have a suitable number of labelled examples, and the reliability of these labels is particularly important. For example, a good minimum starting point is 20 labelled events per class, but 50 labelled events per class is recommended. Models with many hyperparameters to adjust such as DNN usually require many more labelled examples. Additionally, to correctly train a HMM, it is important to have enough continuously labelled time periods to “show” the model enough examples of a transition from tremor to a discrete event, and then back to tremor. It is also important to have many examples of “garbage” events, so that the classifier can recognise and discard them. It is better to have a wide variety of different events within each given class, rather than having many similar events, in order to increase the ability of the models to generalise to other ‘similar’ but not ‘identical’ events.

For all the supervised method, a possible solution to the lack of a sufficient amount of reliable labelled training data could be offered by the generative algorithms. An example of this approach was proposed by Grijalva et al. (2021) with ESeismic-GAN, a GAN model to generate synthetic volcano seismic events, in particular LPs and VTs from Cotopaxi volcano (Ecuador). The authors noted however that GANs maybe not the optimal choice as they are optimised more for computer vision than for time series data.

There is still no agreed-upon format for storing labels. As speech recognition (Rabiner and Schafer 2007) is older and more developed than seismic recognition, one option would be to adopt de-facto standard labelling formats for that domain, e.g., transcription MLF files or any similar text-based format. MLF files can already be created not only by the manual use of a text editor, but also with the GUI provided by programs like Seismo_volcanalysis (Lesage 2009) or geoStudio (Cortés et al. 2023c). Programs

like SWARM (Cervelli et al. 2024) use CSV format for the same task, which can in turn be easily converted by scripts into the MLF or to other standard format that we may adopt.

4.7 Towards Early Warning Systems: Available AI (Open Source) Tools

Once we have selected and stored the best features from our sensors in feature vectors, we can look for software to prepare the data and implement the different ML approaches described above. Open-source software and open access papers are becoming increasingly common, which is great news for anyone interested in using these tools, especially in the Python environment. Many generic libraries are available, but few are specifically tailored to the classification of volcano seismic data. Among the most popular open-source tools for processing and classifying volcano seismic data are ObsPy, a very complete package suitable for any kind of seismic data (Beyreuther et al. 2010), and Msnoise (Lecocq et al. 2014), both of which are available for free download. These tools make it easy for researchers and observatories to process vast quantities of continuous seismic data. The Python Interface for the Classification of Seismic Signals (PICOSS) library (Bueno et al. 2020b) is a powerful and versatile tool for detection, segmentation, and classification of seismic data. It is made up of modular pieces that are independent and adaptable, and the classification is based on two modules that use Frequency Index analysis (Buurman and West 2010) or a multi-volcano pre-trained neural network, in a transfer learning fashion (Bueno et al. 2020a). The already cited REDPy is another interesting open-source software (Hotovec-Ellis and Jeffries 2023). These applications suggest that ML will also provide key analysis tools for volcano-tectonics in the next future (Gudmundsson et al. 2022).

One of the most complicated situations is when an unrest is happening at a volcano for which no previous instrumental data are

available. This calls for the application of models trained at other volcanoes or, even better, using data from multiple volcanoes of similar characteristics. This is the concept at the base of VULCAN.ears, a EU-funded project (Cortés et al. 2019, 2023a). Although the system is theoretically supervised as it is trained with labelled data, from the point of view of the application at a new volcano the model becomes practically unsupervised because several pre-trained models are available (Cortés et al. 2018) and immediately usable with no additional data needed for training (Cortés et al. 2021). The observatory or the researchers can use open-source tools such as pyVERSO (Cortés et al. 2023b), a command interface library based on HTK3 (2023) or its GUI geoStudio (Cortés et al. 2023c). A script also exists, called liveVSR, that can download and classify data from any online seismic data server in realtime (Cortés et al. 2023c).

5 Applications of Machine Learning to Geological, Petrological and Geochemical Data

ML applications to geological, petrological and geochemical data of volcanoes are on the rise, though most of them are limited to variations of cluster analysis, which has been used for example to identify and quantify mixing processes using the chemistry of minerals (Cortés et al. 2007), for studying volcanic aquifers (Morgenstern et al. 2015; Awaleh et al. 2018) or to differentiate magmatic systems (Barette et al. 2017). Supervised CNN with fine tuning were used to extract the areas of exposed stratigraphy in visible images with volcanic outcrops but including e.g., sky and vegetation (Noguchi and Shoji 2023). Not much has been done strictly linked to geological, petrological or geochemical related monitoring, but of course techniques similar to the ones described here can be used for this purpose.

5.1 Petrological Evolution and Whole-Rock Geochemical Characterization

Geochemical analysis can be carried out with several tools, both commercial such as the Statistical Toolbox in Matlab (2023) or open source such as the R platform (R Core team 2018), where some packages were developed, e.g., the CA of GCDkit (Janoušek et al. 2006). In most cases, whole rock major elements and selected trace elements are used in geochemical analyses, with some applications also including isotopic ratios. Many geochemical applications use multiple techniques, often combining both supervised and unsupervised approaches.

Ueki et al. (2018) employ a combination of SVM, RF and SMLR to address the variations in geochemical composition of rocks from eight different tectonic settings. They acknowledge that SVM, as previously used by Petrelli and Perugini (2016), is a powerful method. However, they find that RF has the advantage of indicating the significance of each feature in geochemical discrimination, an important step towards interpretability. The drawback of using RF for tectonic setting discrimination is that the evaluation is based on the majority vote of multiple decision trees, which can make it challenging to obtain a quantitative interpretation of the elements and isotopic ratios. The authors argue that using SMLR as a quantitative discriminant is the most effective method, as it allows assigning a probability of belonging to a given group (in this case, a tectonic setting) while also identifying the importance of each feature. This approach represents a significant advancement in the discrimination of geochemical signatures of different tectonic settings. These have traditionally been assessed using binary or ternary diagrams, such as those in Pearce and Cann (1973) and Schandl and Gorton (2002), which are useful for large sample sets but cannot differentiate tectonic settings with complex magma evolution. In recent years, multi-element variation

diagrams (Li et al. 2015) and techniques such as DT (Snow 2006) and LDA (Verma and Armstrong-Altrin 2013) have been proposed to more accurately assign tectonic settings based on rock geochemistry. Ueki et al. (2018) demonstrate that a set of 17 elements and isotopic ratios is necessary to clearly identify a tectonic setting based on rock sample geochemistry. Additionally, two new discriminant functions were proposed to discriminate the tectonic settings of mid-ocean ridges and oceanic plateaus. Ten datasets were used to evaluate the discrimination quality of LDA and canonical analysis, including original concentrations, isotopic log-ratio transformed variables, and all 10 major elements as well as all 10 major and 6 trace elements (Verma and Díaz-González 2020).

Zhao et al. (2019) used RF and DNN to analyse the origin of volcanoes in Northeast China using full chemical compositional data. The results of the analysis showed that these volcanoes were associated with the Pacific slab, subducting below Japan, reaching a depth of approximately 600 km under eastern China and extending horizontally up to Mongolia. Furthermore, the study identified a boundary between volcanoes fed by fluids and melts from the slab and those that were not related to it, which was located at the westernmost edge of the deeply buried Pacific slab.

Esposito et al. (2021) used SOM to analyse geochemical data from the Italian Ischia, Vesuvius, and Campi Flegrei volcanoes, without using any prior knowledge of geochemical or petrological characteristics. The SOM toolbox for Matlab (2023) was used to perform two tests. The first test used major elements and selected trace elements to find similar evolution processes and the second test was used to investigate the magmatic source. A vector containing a selection of ratios between major and trace elements was adopted. This method is useful because it can differentiate rock samples that were only comparably distinguished by 2D diagrams of isotopic ratios, which means it can achieve comparable results with less expensive geochemical data.

5.2 Genesis of Deposits and Stratigraphic Correlation

Brandmeier and Wörner (2016) used the Compositional Data Package (CoDaPack 2024) software and a combination of unsupervised (CA) and supervised (LDA) learning techniques to examine the compositional variations of ignimbrite magmas in the Central Andes. They aim to use these methods as a tool for correlating ignimbrites. The statistical software Statistica (Weiß 2007) was used for both CA and LDA analyses.

Monitoring volcanoes requires a thorough understanding of the various processes and characteristics that influence their activity. One valuable tool is the analysis of clast morphology, which provides information about the genesis, transport, and depositional processes of volcanic materials. While the application of ML techniques in this area is still in its nascent stages, pre-processing techniques such as the Radon Transform can be used as a first step towards efficient definition of feature vectors for classification. For example, Moreno Chávez et al. (2020) applied this method at Colima volcano (Mexico), demonstrating the potential of this approach in the analysis of clast morphology.

Correlating tephra and determining their origin from specific volcanoes is a challenging task, especially in regions where several volcanoes have had explosive eruptions in a brief period of time. This is made more difficult when the volcanoes have similar geochemical and petrographic compositions. Despite this, determination of glass and mineral compositions by electron microprobe analysis and whole-rock geochemical analyses are commonly used to make these correlations. However, these methods may not be entirely accurate as they may mask important diagnostic variability.

While identification of tephra volcanic sources remains an open issue, recent research has shown that ML techniques can provide accurate correlation results (Bolton et al. 2020). For example, LDA (Beaudoin and King 1986; Bourne et al. 2010) and SVM (Petrelli et al.

2017) have been employed with remarkable success in this regard. However, it is worth noting that SVM may not always be suitable for specific cases; Bolton et al. (2020) suggest that for their case study on tephra from Alaska volcanoes, the combination of ANN and RF were the most effective ML techniques to apply. They use the R software (R Core Team 2018) to implement these methods and emphasize the advantage of producing probabilistic outputs.

5.3 Prediction of Missing Elements and Integration in Monitoring

ML techniques have the potential to provide valuable contributions in the field of geochemistry, for instance in the prediction of unknown element concentrations based on a large dataset of known elements. Hong et al. (2019) applied a combination of ML techniques to predict the concentrations of Rare Earth Elements (REE) in Ocean Island Basalts (OIB) using RF. The study used 1283 analyses, using 80% for training and the remaining 20% for validation. The results indicated that the predictions were accurate for the Light Rare Earth Elements (LREE), however, it was suggested that the accuracy could be further improved by using a larger dataset for training. An alternative approach may be to consider in the training process not only major elements, but also other trace elements obtained through the same analytical method. REE distribution patterns were studied by Ambrosino et al. (2022) with a combination of Lasso regression and robust PCA.

ML and DL can improve the estimation of the volcanic sulfur dioxide (SO_2) emissions and better evaluate risks for health and aviation, as we discuss in the section dedicated to remote sensing. If we consider the task of volcano monitoring, it is important to note that also for geochemistry ML methods should be always integrated with other techniques such as fieldwork, petrographic observations, and traditional geochemical studies to gain a more comprehensive understanding of the volcano under

investigation. However, it is worth noting that while big data are easy and cheap to acquire in seismology or geophysics in general, this is not the case for geochemistry. Nevertheless, also when applying ML techniques to the geochemistry of volcanic rocks, a minimum dataset size is required. The literature suggests that a set of 250 analyses is sufficient, but it is also possible to work with smaller datasets if necessary. Of course, having thousands of examples would greatly improve the results.

6 Applications of Machine Learning to Remote Sensing Data

Although seismology remains one of the key volcanic monitoring tools, ground-based, drone-based, plane-based and satellite-based remote sensing data can be acquired and processed for monitoring; ML tools can be applied to all these data.

There is a wide range of remote sensing techniques, that differ on the base of the location and type of sensor used (e.g. active vs. passive), the type of radiation used (visible, infrared, etc.). Active remote sensing techniques include Radio Detection and Ranging (RADAR) (using radio waves) and Light Detection and Ranging (LIDAR) (using laser light), while passive remote sensing examples include visible light, infrared optical and thermal, multi-spectral, hyper-spectral imaging.

An important active method, which can be ground-based or satellite-based, is SAR, which can provide high-resolution images by emitting microwave signals and analysing the return signal. SAR can operate in various modes, providing different levels of resolution and coverage. Interferometric Synthetic Aperture Radar (InSAR) uses two or more SAR images of the same area acquired at different times or from different viewpoints to study Earth surface deformation (e.g. due to magma accumulation) and landscape changes (e.g. due to new volcanic deposits). It is therefore a technique widely applied in volcano monitoring (see Pinel et al.

2014 for a review) and has great potential especially where images are freely available.

6.1 Satellite-Based Analysis

Satellite remote sensing technology is particularly important for volcanoes located in areas where ground monitoring is scarce or non-existent. For example, in Latin America, 202 out of 319 Holocene volcanoes did not have seismic, deformation, or gas monitoring by 2013 (Ebmeier et al. 2019). ML methods can be used e.g. for the initial processing (data cleaning and preparation) of single satellite data or fully exploit integrated multi-disciplinary, multi-satellite datasets (Ebmeier et al. 2019). An example is the advanced CNN-based speckle filtering of SAR images that was developed by Davis et al. (2020) Sentinel-1 data, and by Valade et al. (2023) for TerraSAR-X data.

At a higher level, a complex-valued CNN was proposed to extract areas with land shapes similar to given samples in InSAR. This approach was demonstrated by grouping similar small volcanoes in Japan (Sunaga et al. 2018). The ML algorithm ICASAR, based on ICA applied to Sentinel-1 InSAR data and applied to Sierra Negra volcano as a case-study, can detect possible volcanic unrest due to both a change in the rate of a preexisting signal and the emergence of a new signal (Gaddes et al. 2019). When possible, ICASAR can be combined with time series of GPS data to help the modelling. The use of CNN was more recently proposed by Gaddes et al. (2024), to differentiate styles of volcanic deformation and to better determine the size of a deformation. The authors also made available a new database of labelled Sentinel-1 interferograms for multiple volcanoes named VolcNet, that could be used to train additional models. A transfer learning strategy was applied to ground deformation in Sentinel-1 data (Anantrasirichai et al. 2018) and a range of pre-trained networks were tested, including AlexNet (Krizhevsky et al. 2012) that provided the best results, again demonstrating the effectiveness

of ML techniques on satellite data for volcano monitoring.

The Copernicus Programme of the European Space Agency (ESA) and the European Union (EU) has recently contributed by producing the Sentinel-2 multispectral satellites, which can provide high-resolution satellite data for disaster monitoring to complement previous satellite images like Landsat. The use of Sentinel-2 data also benefits from free access policy and can be processed by ML techniques such as SVM and RF (Phiri et al. 2020) or clustering (Corradino et al. 2019).

Ley et al. (2018) trained a GAN on aligned Sentinel-1 and Sentinel-2 image pairs. Learning the transformation from SAR images into optical images forced the GAN to distinguish between different land surfaces. The resulting pre-trained model was then used to build a classifier with fewer parameters that can be trained with a smaller amount of labelled data. The possible applications for multi-parameter volcano monitoring are significant, as GAN capabilities to distinguish different land surfaces with fewer training inputs can help e.g. to identify and classify more rapidly new volcanic deposits.

The global volcano monitoring platform MOUNTS (Monitoring Unrest from Space) (Valade et al. 2019) uses ML techniques to analyse multisensor satellite-based imagery (Sentinel-1 SAR, Sentinel-2 Short-Wave InfraRed SWIR, Sentinel-5P TROPOMI) with the aim of detecting signs of volcanic unrest. This platform uses several CNN to automatically detect surface deformation and filter speckle in interferograms and SAR amplitude images from global volcanoes. ML enables efficient, consistent monitoring of numerous volcanoes, reducing manual analysis and accelerating hazard detection. For instance, Biggs et al. (2022) studied the ability of CNN for detecting deformation at volcanoes by processing a 2015–2020 dataset of about 600 k Sentinel-1 images of more than 1000 volcanoes.

One of the key advantages of using ML in volcano monitoring is in fact the ability to process substantial amounts of data from various

sources. MOUNTS's aim is to combine satellite imagery, seismicity, and gas measurements to create consistent multi-parametric datasets over a large number of active volcanoes worldwide, which will allow to use ML approaches to identify unrest and/or eruptive patterns. The platform also incorporates a classification algorithm to identify specific types of volcanic unrest and estimate the level of potential hazard. MOUNTS also uses computer vision techniques to automatically detect changes in thermal signatures and gas emissions at the volcanoes. The ML plugins in the MOUNTS platform can improve the quality of the data, e.g., filter SAR images with CNN, and recover more accurate signals, e.g., detection of deformation in INSAR interferograms with CNN, or cluster gas plumes with CA algorithms. This will hopefully take us closer to real-time monitoring and early warning of potential eruptions. Results can be visualised on an open-access website and they are already used by several volcano observatories worldwide as an additional support to their monitoring strategies. The efficiency of the system was already tested on several eruptions (Erta Ale 2017-Ethiopia, Fuego 2018-Guatemala, Kilauea 2018, Anak Krakatau 2018-Indonesia, Ambrym 2018-Vanuatu, and Piton de la Fournaise 2018–2019-La Réunion island, France) (Valade et al. 2019).

6.2 Detecting Plumes, Lava Flows and Pumice Rafts

Opio et al. (2023) simulated larger SO₂ plumes that spread to over 500 km from Mount Nyiragongo (border Democratic Republic of Congo—Rwanda), using the Weather Research and Forecasting model coupled with chemistry (WRF-Chem). An autoencoder based on a deep CNN was used to correct the bias that WRF-Chem showed with respect to satellite Ozone Monitoring Instrument observations.

Markus et al. (2023) proposed an open source SO₂ plume classifier that processes data from the Sentinel-5 TROPOMI instrument, using computer vision image processing

and segmentation together with ML techniques such as DBSCAN clustering. Several plumes were analysed as case studies, emitted in the atmosphere in 2021 by Etna (Italy), Sangay and Reventador (Ecuador), Sabancaya and Ubinas (Peru), Scheveluch and Klyuchevskoy (Russia), as well as Ibu and Dukono (Indonesia).

Torrìsi et al. (2022) demonstrated on Etna that a supervised SVM can detect, track and map automatically volcanic ash clouds in near real-time, processing 2020–2022 Thermal InfraRed (TIR) bands acquired by the geostationary MSG-SEVIRI (Meteosat Second Generation—Spinning Enhanced Visible and Infrared Imager).

Another key application of remote sensing is the mapping of lava flows from satellite imagery. Li et al. (2017) applied RF to 20 individual flows and 8 groups of flows of similar age using a Landsat 8 image and a Digital Elevation Model (DEM) of Nyamuragira volcano (Congo) with a 30 m resolution. The research found that despite the spectral similarity, lava flows of contrasting age could be well discriminated and mapped through image classification, highlighting once again the potential of the use of ML with remote sensing technology also for monitoring. Corradino et al. (2019) used a K-medoids unsupervised clustering technique (Kaufman and Rousseeuw 1990) to discriminate 2017 and 2018 lava flows at Mt. Etna imaged in the MultiSpectral Imager (MSI) onboard Sentinel-2 satellite. Pixels in a scene are classified and then grouped into classes. Bands at the spatial resolution of 10 m (bands 2, 3, 4, 8) are used as input to the classifier. Corradino et al. (2021a) used K-means and SVM to map lava flows at Etna (Italy) and Fogo Island (Cape Verde) using both optical and SAR satellite images. Corradino et al. (2021b) used again a K-means unsupervised classifier on SAR images at Stromboli to study its explosive activity between 2018 and 2021, distinguishing between paroxysms and major explosions. At INGV-TechnoLab in Catania (Italy), Amato (2022) developed a Google Earth Engine (GEE) software to detect lava flows at Etna, using freely accessible satellite images (Sentinel-1, Sentinel-2, Landsat-8,

EOS AM-1 Terra and EUMETSAT MSG) and ML tools such as K-means, SVM, Classification and Regression Trees (CART) and Minimum Distance (MD). SVD is the approach chosen by Del Negro et al. (2022) to characterise all the volcanic products (lava flows, tephra, clouds) emitted during a lava fountaining episode at Etna. Again, this was done using GEE.

Modelling lava flows or other eruptive phenomena could benefit from many simulations produced by generative algorithms. Yamaguchi and Cabatuan (2017) generated lava flow video frames using Deep Convolutional GANs and VAEs, using YouTube videos as training inputs, with VAEs showing the best results.

The problem of detecting submarine eruptions using satellite images in the GEE was tackled by Zheng et al. (2022), who used a RF approach for the detection of pumice rafts. However, the authors point out that these rafts are not always related to a new eruption but rather to the remobilisation of pumice from previous eruptions.

6.3 Ground-Based Analysis

Mount Erebus, located in Antarctica, is known for its persistent lava lake displaying Strombolian activity. Due to its remote location, automatic methods for detecting these explosions are highly desirable. Dye and Morra (2020) employed a CNN trained using infrared images captured from the crater rim. The images were “labelled” with the help of accompanying seismic data, which was not used during the subsequent automatic detection process. This approach demonstrates the potential for using CNN in combination with remote sensing techniques for monitoring volcanic activity in remote locations.

In fact, ground-based videocamera systems are increasingly used for monitoring volcanoes, providing a low cost and handy tool in emergency phases, although the processing of large data volumes from continuous acquisition still represents a challenge, which once again calls for the application of ML techniques. Witsil

and Johnson (2020) used MLP to process video camera images, mainly from Villarrica volcano, Chile to categorise the observable activity into different classes. Guerrero Tello et al. (2022) provide an interesting example of detection and segmentation of volcanic ash plumes using CNN at Etna (Italy). Two architectures, the seg-Net and the U-Net, were used for the processing of 560 visible video cameras images from a ground-based network during the eruptive episode of 24 December 2018. In the pre-processing phase, data labelling for computer vision was used, adding one meaningful and informative label to provide eruptive context and the appropriate input for the training of the ML tool. The automatic detection of plumes helps to significantly reduce the data storage and the semantic segmentation allows volcanic plumes to be tracked and parametrised automatically.

Corradino et al. (2020) proposed a system based on DT and a Bag of Words (BoW) approach able to recognise and classify in real time eruptive activity occurring at Etna (Italy) by analysing ground infrared thermal images. The BoW model, often used in image category classifications (Zhang et al. 2010), represents images as occurrence histograms of a bag of “visual words”, used in turn as a training set for the classifier. DT decides the visibility level of the monitored area before the classifier distinguishes explosions, lava flows and degassing episodes.

Cirillo et al. (2022) developed the software “StaTistical Analysis clusteRed ThERmal Data” (STARTED) to process and cluster images recorded by handheld thermal cameras by K-means and DBSCAN, finally producing statistics to recognise fluctuations in temperature.

7 Other Applications of Machine Learning to Volcanology and Monitoring

Significant is the landslide hazard associated with volcanoes. DNN models were proposed to assess landslide susceptibility in Vietnam,

and showed significant better performance compared to other ML methods such as MLP, SVM, DT and RF (Bui et al. 2020). Therefore, for landslide susceptibility mapping of active volcanoes, the use of DNN could be an interesting approach. Landslide susceptibility was also estimated using supervised LR models (Pradhan and Lee 2010), an approach also used, together with RF, to estimate the ending date of an eruption at Telica (Nicaragua) and Nevado del Ruiz (Colombia) using volcano seismic data (Manley et al. 2020).

Debris flow events are one of the most widespread and dangerous natural processes, not only on volcanoes, but also in mountainous environments in general. Starting from a case study on Changbai Shan volcano, China, Si et al. (2020) recently proposed a methodology that combines the results of deterministic and heuristic/probabilistic models for susceptibility assessment, where the heuristic/probabilistic component is studied using RF models.

Relatively few studies analysed the electrical activity during volcanic eruptions. LR was used by Behnke et al. (2022) to classify two distinct types of such activity: vent discharges and lightning. Vent discharges are small, lasting for seconds at the onset of an eruption, and differ from lightning according to their discharge physics. After those, lightning occurs within the eruption column.

Sometimes approaching a volcano can be dangerous, and automatic robots can be a feasible solution for monitoring and/or for deploying monitoring instrumentation. Again, the need arises for ML tools that help the robot to navigate safely on the volcano. A recent example of this kind of approach was presented by Evita et al. (2022) for Indonesian volcanoes. This is one of the applications where RL could significantly enter the field of volcano monitoring, robotics being one of the key applications.

Handling volcano unrest also requires effective communication and education methods. In this regard, the Museum of Mineralogy, Petrography and Volcanology of the University of Catania has implemented a communication system based on visitors' personal experience

and learning through play. One example of this is a web application called I-PETER: Interactive Platform to Experience Tours and Education on the Rocks. This platform includes a labelled dataset of images of rocks and minerals that can also be used for petrological investigations using ML techniques (Sinitò et al. 2020).

Muon imaging has been successfully used by geophysicists to study the internal structure of volcanoes. One example is Etna (Italy) (Carbone et al. 2013). Muon imaging, essentially an inverse problem, can benefit from the application of ML techniques, such as ANN and CA (Yang et al. 2018).

Volcanoes on other planets have also been mapped using combinations of supervised and unsupervised ML techniques. For example, a ML paradigm has been developed for the identification of volcanoes on Venus (Burl et al. 1998). Other studies have detected and classified manually labelled Martian landforms, including volcanoes, using topographic data such as DEMs and associated derivatives obtained from orbital images (Ghosh et al. 2010). The classification is made using different supervised methods: Naive Bayes, Bagging with DT and SVM. This provides once again ideas on the possibilities of remote sensing combined with ML for monitoring particularly remote volcanoes on Earth.

8 Conclusions and Future Directions

ML techniques play and will play an increasingly important role in studying and modelling volcanoes, as well as monitoring them and evaluating their hazards. The increasing number of monitoring equipment installed on volcanoes can result in a lot of data, but often processing it in real time is impractical. ML can be therefore very useful in sorting through big data to find subtle patterns that could indicate unrest, hopefully well before eruptions. One important issue is that we need to build models that can be applied to different volcanoes, based on limited or no previous data. Concepts like

transfer learning can be important in making this possible.

There are approaches to ML that at first sight seem far from the problems of signal analysis and monitoring. An example is the Chat Generative Pre-Trained Transformer, better known as ChatGPT (2024), a chatbot developed by OpenAI launched in November 2022 which has impressed for the accuracy of its outputs in many topics (and lack of accuracy in others). ChatGPT belongs to the family of LLM and it applies supervised and Reinforcement Learning with Human Feedback (RLHF) (Christiano et al. 2017). These techniques allow to write (reasonable drafts of) computer code, especially in Python. New, often unexpected, applications of ChatGPT continue to appear, as described in Sect. 3.4 (Generative algorithms), and we see therefore possible that also applications to the monitoring of continuous volcanic data, at least through the assisted development of computer code, will appear soon. Another possibility of application is to represent volcanic signals with words of a suitable vocabulary, a concept similar to the BoW used for images (Zhang et al. 2010), which can then be used by tools like ChatGPT to classify, infer and forecast. The concepts at the base of RLHF could also be used in order to enhance the performance of classifiers (e.g., of volcano seismic events), especially when using a set of human-produced training labels that are not perfectly reliable, a not uncommon case. This can somehow be combined with the active learning approach.

Many times the output of ML tools are unexplained, and the tools behave like “black boxes”. Although this can still be useful, a major step forward can be taken by adding interpretability to the results provided by ML techniques. This is why Argumentation and eXplainable Artificial Intelligence (XAI) are becoming increasingly hot research topics (Vassiliades et al. 2021). Only with interpretability, the application of sophisticated algorithms at different levels of abstraction, from classifying individual seismic events to recognising distinct levels of unrest and possible outcomes, can really enhance our understanding of volcanic activity and improve

our ability to forecast what the volcano will do next.

Another approach that has a lot of potential to be exploited is the one of PINN. Wave propagation, active seismic data processing, full waveform inversions, crustal deformation, earthquake processes (Okazaki et al. 2022) have already been tackled with this approach, so that volcanology and volcano monitoring could reasonably become a future application. There is also the potential to develop RL models that optimise monitoring using multiparametric experimental data or the logistics of the emergency response to (volcanic) disasters. Also MeL has the potential to enhance models of volcanic activity using new incoming data and comparing it to the output of previous models, or to improve early warning systems by learning new ways of analysing monitoring data by examining patterns in new data.

The routine use of ML tools at volcano observatories should be promoted by providing easy installation procedures and easy integration into existing monitoring systems. Open-source software should be always chosen whenever possible, while observatories should easily provide good, open access, training data to ML developers, researchers, and data scientists to improve the models in a virtuous circle. The variability of volcanic eruptions requires numerous and diverse observations for efficient forecasting. Volcanological databases are therefore important resources that help answering questions which may not be answerable by single datasets. Large-scale or synoptic studies are increasingly accessible using ML applied to those often-complex databases. Andrews et al. (2022) analyse the complexity of the existing volcanological database landscape including the issues of data standardisation and long-term growth and sustainability of databases. Easy availability of open access data, both from the ground and from satellites, remains a key step for building reliable training sets in the different fields of volcanology, which will allow “scientific competition” between research groups using different ML approaches and make a direct comparison of results easier.

Acknowledgements This review could not have been possible without the innumerable past discussions with RC's former students, coauthors and colleagues, among them: Luca Barbui, Moritz Beyreuther, Susanna Falsaperla, Art Jolly, Horst Langer, Philippe Lesage, Bastian Steinke and Joachim Wassermann. This review is dedicated to the memory of Olivier Jaquet.

This review greatly benefitted from the experience of VULCAN.ears, a project funded under the European Union's Horizon 2020 research and innovation program under the Marie Skłodowska-Curie Grant Agreement No. 749249.

The authors wish to express their most sincere gratitude to the reviewers Guillermo Cortés Moreno and Sébastien Valade, and to the editors Corentin Caudron and Zack Spica for their invaluable comments that greatly improved the quality of this chapter.

Conflict of Interest The authors declare no conflict of interest.

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Monitoring Lightning and Electrification in Volcanic Plumes

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Abstract

Detection of the electrical discharges and, more fundamentally, the electrification from volcanic plumes is an emerging capability for volcano monitoring. In addition to being able to detect an explosive eruption, such measurements also provide insight into volcanic processes. Volcanic lightning monitoring can be achieved through varying levels of complexity. At the lowest complexity, an observatory can use low-cost global lightning data sets for eruption detection and characterization, while at the highest complexity local lightning sensors can be installed to improve the level of observational detail and response times. This chapter provides background about volcanic lightning and plume electrification, information concerning the relevant instrumentation to detect lightning and

electrified plumes, examples of how lightning can be used to understand eruptive processes, and a guide to implementing volcanic lightning detection into a monitoring scheme.

1 Introduction

The electrification of volcanic plumes and the occurrence of volcanic lightning and other volcanic electrical discharges create detectable signatures that can be employed for volcano monitoring. Measurements of electrical activity provide a means to not only identify volcanic activity in near real-time, but to investigate and understand volcanic processes as well. Electrical activity can be detected through many different methods and at distances ranging from kilometers to thousands of kilometers, offering flexibility for incorporation into operational monitoring schemes. This chapter aims to guide the reader through the basics of lightning physics, volcanic lightning, as well as the relevant volcano terminology. In addition, we provide information about lightning detection methods and show how lightning and other observations of electrical activity can be used practically in volcano monitoring. The study of lightning and atmospheric electricity is outside the conventional realm of volcanology; therefore, we aim to provide enough detail to initiate new researchers to the field of volcanic lightning. Our goal is to

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make volcanic lightning monitoring methods more accessible to volcano observatories around the world.

2 Terminology and Key Physical Processes

The terminology used within lightning physics and volcanology can be overwhelming. Many common terms are synonyms, while some are more colloquial. For the purposes of using lightning data to monitor or study volcanoes, we provide a list of relevant terms and their succinct definitions with references in Table 1. We provide more background on these definitions in Sects. 2.1–2.3. In addition, some definitions for lightning terms can be found online at the American Meteorological Society Glossary of Meteorology (<https://glossary.ametsoc.org/wiki/Welcome>). For volcanology terms, we refer readers to the Encyclopedia of Volcanoes (1st and 2nd editions; Sigurdsson et al. 1999, 2015).

2.1 Overview of Lightning Physics

Lightning is a large-scale manifestation of the electrical breakdown of air, which serves to neutralize charge in a thunderstorm or volcanic plume. For a detailed review of the physics of lightning, we refer the reader to Dwyer and Uman (2014). Here we provide a simplified explanation of lightning and how it propagates. Figure 1 provides a graphical illustration of some of the terms explained here.

Lightning is composed of hot conductive channels of plasma called “leaders”. The leader is bidirectional and bipolar: one end is negatively charged, while the other end is positively charged. At each end of the flash, leaders branch and form networks much like a tree. A lightning leader propagates due to ionization ahead of the leader tip. This ionization occurs in streamers, which are filamentary, weakly conducting plasma channels. Streamers serve to provide an electric current into the leader, which keeps the leader conductive. The electric field at the tip of

the leader is thus very high to enable this ionization. Leaders are often called “stepped-leaders”, because negative-polarity leaders grow in discrete steps. Positive leaders, on the other hand, generally propagate continuously, though stepping behavior has been observed in upward positive leaders (e.g., Biagi et al. 2011).

An even more foundational type of electrical breakdown is the electron avalanche. An electron avalanche is caused by collisions between free electrons and air molecules in an ambient electric field. These collisions can liberate electrons from the air molecules, which in turn can collide with other air molecules and ionize more electrons. If the electric field is strong enough, the rate of production of new electrons from collisions will outpace the rate of re-attachment of the electrons with air molecules, thus creating an avalanche of free electrons. Therefore, in the hierarchy of electric discharges we have electron avalanches, which under sufficient conditions evolve into streamers, which in turn can evolve into leaders. A corona discharge can be either electron avalanches or streamers, and they often occur around objects that enhance the local electric field, such as grass, trees, or man-made conductive structures (Standler and Winn 1979).

When lightning travels out of a cloud and makes a connection with ground it is called cloud-to-ground (CG). When lightning propagates only within the charged regions of a cloud it is called intracloud (IC). However, it is also common to use the more general term ‘cloud flash’ for lightning that doesn’t make a connection with ground. CG lightning can initiate from the ground and propagate upward into a cloud, but in thunderstorms it is more commonly initiated in a cloud and moves toward ground. We note CG and IC lightning are fundamentally the same, in terms of their physics of propagation. Lightning initiates between regions of charge, as the electric field is highest at these boundaries, and each end of the bipolar leader propagates towards a region of opposite polarity. More specifically, the negative end of the leader propagates into regions of net positive charge, while the positive end of the leader propagates into regions of net negative charge. The

Table 1 Terminology used in lightning physics and volcanology

Term	Definition	Synonym	References
Lightning physics terms			
Electrical discharge	Any process that results in the flow of current in a gas		Bazelyan and Raizer (2000)
Leader	A type of electrical discharge consisting of a conductive channel of plasma		Bazelyan and Raizer (2000)
Streamer	A type of electrical discharge consisting of weakly conducting, filamentary plasma channels		Nijdam et al. (2020)
Lightning	A complex electrical discharge consisting of leaders and streamers that transfers charge within a cloud, or between a cloud and ground	Lightning discharge, lightning flash, flash	Dwyer and Uman (2014)
Cloud to ground (CG) flash	A lightning discharge in which a leader makes a connection with ground		Uman (1987)
Cloud flash	A lightning discharge that does not connect with ground	Intracloud (IC), in-cloud flash	Uman (1987)
Return stroke	The flow of current and burst of luminosity along a leader channel after its connection with ground in a cloud-to-ground flash	Stroke	Uman (1987)
Dart leader	Reionization of an existing leader channel that is connected with ground, resulting in subsequent return strokes		Uman (1987)
Multiplicity	The number of return strokes in a CG lightning flash		
Cloud pulse	A pulse of current transferring charge within a cloud; occurs in both cloud flashes and cloud-to-ground flashes	In-cloud pulse	
Sferic	A colloquial term for the electric field signature created by cloud pulses or return strokes	Atmospherics	
Peak current	Measure of maximum current from a CG or cloud pulse, typically derived from low frequency or very low frequency lightning electric or magnetic field measurements		Orville (1991)
Vent discharge	Streamer discharge occurring in the gas-thrust region of an eruption column		Behnke et al. (2018)
Continual radio frequency (CRF)	The collective radio frequency signal arising from repeated vent discharges lasting seconds or longer	Continual radio frequency impulses	Thomas et al. (2007)
Near-vent lightning	Lightning occurring in or near the gas-thrust region of the eruption plume		Thomas et al. (2010)
Plume lightning	Lightning occurring in the convective regions of an eruption plume		Thomas et al. (2010)
Volcanology terms			
Ashfall	Particles that sediment out of a volcanic plume and ultimately form a deposit on the ground; Fig. 2	Fallout, airfall, tephra fall	USGS glossary ¹¹

(continued)

Table 1 (continued)

Term	Definition	Synonym	References
Caldera	A basin-shaped depression typically much larger than a crater (>2 km diameter), formed by subsidence into a partly drained magma reservoir		USGS glossary ¹¹
Crater	The morphological depression created by outward expulsion of volcanic material		USGS glossary ¹¹
Explosive eruption	An eruption dominated by emission of volcanic gas and tephra into the atmosphere (as opposed to an effusive eruption, which mainly produces lava flows or domes)		USGS glossary ¹¹
Eruptive event	An individual phase of activity associated with a continuing eruption (with 'continuing' defined as no time breaks of 3 months or more)		Global volcanism program ²
Plume	General term for airborne volcanic emissions that are still connected to the eruptive source		Sparks et al. (1997)
Column	The vertically oriented stalk of airborne emissions and gas rising from explosive volcanic activity		Sparks et al. (1997)
Pyroclastic density currents (PDCs)	Ground-hugging flows of hot ash and gas; Fig. 2b	Pyroclastic currents, flows, surges	Druitt (1998)
Co-PDC plume	Elutriated ash and gas that lofts buoyantly from ground-hugging pyroclastic density currents (PDCs); Fig. 2b	Co-ignimbrite plume (specific to pumice-dominated eruptions)	Engwell et al. (2016)
Gas-thrust region	Momentum-driven lower portion of an eruption column; Fig. 2a	Jet region	Sparks et al. (1997)
Convective region	Portion of an eruption column that is less dense than the surrounding air and rises buoyantly; Fig. 2		Sparks et al. (1997)
Weak plume	Emissions that rise too slowly to overcome the background wind field, resulting in a bent-over shape without an umbrella cloud; Figs. 2c and 8d	Wind-dominated plume	Carey and Bursik (2015)
Strong plume	Emissions that rise significantly faster than background winds, forming a vertical column and umbrella cloud (as opposed to a weak or wind-dominated plume); see Figs. 2 a,b and 8c	Plinian plume, buoyancy dominated plume	Bonadonna et al. (2005)
Umbrella cloud	Radially expanding, lateral intrusion at the top of an eruption column; see Fig. 2a, b	Mushroom cloud	Carey and Sparks (1986)
Tephra	Any volcanic particle ejected from a volcano, regardless of size, composition, or process	Pyroclast	USGS glossary ¹¹
Volcanic ash	Erupted rock particles <2 mm diameter		USGS glossary ¹¹

(continued)

Table 1 (continued)

Term	Definition	Synonym	References
Phreatomagmatic eruption	Explosive volcanism with substantial involvement of external water (e.g., lake, ocean, or glacier, or aquifer)	‘Wet’, water-rich, or hydrovolcanic eruption	Houghton et al. (2015)
Magmatic eruption	Explosive volcanism driven primarily by internal volatiles transported in the magma	‘Dry’ eruption	Cashman and Scheu (2015)
Phreatic eruption	Explosive volcanism without direct involvement of fresh magma and resulting in a gas-rich plume; ash particles may be present, but represent pulverized fragments of older rock	Steam eruption, hydro-thermal explosion	Browne and Lawless (2001)
Vent	General term for an opening at the Earth's surface through which magma erupts or volcanic gases are emitted		USGS glossary ¹

¹ U.S. Geological Survey Volcano Hazards Program Glossary: <https://volcanoes.usgs.gov/vsc/glossary/>

²Global Volcanism Program: https://volcano.si.edu/gvp_currenteruptions.cfm

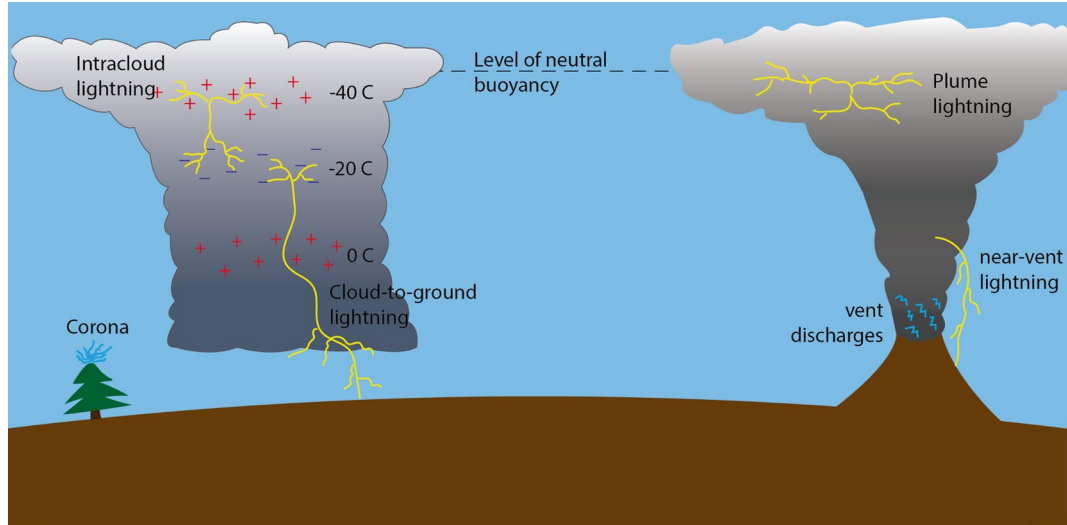


Fig. 1 Cartoon of an idealized thunderstorm and volcanic plume, showing basic types of electrical activity. While the level of neutral buoyancy for a thundercloud is at or near the tropopause, the level of neutral buoyancy for a volcanic plume can be lower or significantly higher than the tropopause. Temperature ranges for a normal polarity tripole are shown for a thunderstorm, but a conceptual model does not yet exist to relate the thermal structure of a volcanic plume to its charge structure.

Intracloud and cloud-to-ground lightning occur in both thunderstorms and volcanic plumes, and both plume lightning and near-vent lightning can manifest as IC or CG. The volcano-specific terms plume lightning and near-vent lightning have been used to differentiate the locations within a plume where lightning is occurring. Vent discharges refers to streamer discharges that occur within the gas-thrust region of a plume

manifestation of lightning into an IC or CG flash depends on where the flash is initiated and the particular arrangement and quantities of positive and negative charges in a cloud.

When a leader reaches ground, whether it is of positive or negative polarity, a large current flows along the connecting leader channel, effectively removing a net charge from a cloud. This pulse of current is called a return stroke. If the polarity of the leader reaching ground is negative, the polarity of charge transferred to ground is negative, and is thus described as a negative CG. Alternatively, one can think of this process as adding positive charge to the cloud. A positive CG occurs when a positively charged leader connects with ground, thus removing positive charge from the cloud. The multiplicity of a CG refers to the number of return strokes in a CG lightning flash. After the initial leader/return stroke sequence, subsequent “dart” leaders may propagate through and re-ionize the original leader channel that was connected with the ground. Each time a subsequent dart leader reaches ground, another return stroke, and thus transfer of current, occurs. Negative CGs are characterized by having multiple return strokes, while positive CGs have only one return stroke.

Though intracloud lightning does not remove charge from a cloud—it merely rearranges it—it can also be considered to have a polarity, depending on the orientation of the charge structure that the leaders are propagating into. Lightning leaders propagate into regions of charge that have a polarity opposite to that of the leader itself, and it is the direction of propagation of the negative leader that dictates the polarity of the discharge. An IC flash is considered positive when the negative leader propagates upward into positive charge, and negative when the negative leader propagates downward into positive charge. Thunderstorms typically have two or three dominant, vertically stratified layers of charge. A so-called normal polarity tripole has three layers of charge arranged vertically with positive at the top, negative in the middle, and positive at the bottom (e.g., Williams 1989). Such a configuration is depicted in Fig. 1, and leads to the production of positive

ICs in the upper dipole. Similar to the return stroke in a CG flash, strong pulses of current also occur along leader channels in IC flashes through a variety of processes. We direct readers to Bruning et al. (2014) for a discussion of how thunderstorm charge structures, and thus the polarity of lightning, vary depending on environmental conditions.

2.2 Overview of Volcanic Plume Dynamics

There are many eruptive processes that may lead to electrification, but they all involve airborne emissions of gas, with or without volcanic ash. The dynamics of a volcanic plume and its interaction with the surrounding environment determine the resulting electrification processes and hazards, which may include ashfall deposition on downwind communities, transport of airborne particles threatening aircraft (Guffanti and Tupper 2015), and generation of potentially lethal pyroclastic density currents (PDCs). In this section we provide an overview of the plume dynamics and microphysics relevant to monitoring volcanic electrical activity.

The typical sketch of a strong volcanic plume shows a sustained, ash-rich column rising directly from a volcanic vent (Fig. 2a). As the high-speed mixture of gas and particles enters the atmosphere, it is initially denser than the surrounding air and powered by momentum (Sparks et al. 1997). This region is defined as the gas-thrust (or jet) region, typically encompassing the lowermost hundreds of meters to a several kilometers depending on the scale of the eruption. The rising column ingests air by turbulent entrainment, becoming more dilute and buoyant as it transitions to convective ascent. High-intensity eruption columns typically overshoot the level of neutral buoyancy and cascade back down, spreading out as a gravity-driven intrusion known as an umbrella cloud (Woods and Kienle 1994). Umbrella clouds from large eruptions can transport ash in all directions including upwind, dramatically influencing the patterns of ash dispersal (Mastin et al. 2014; Mastin and Van Eaton

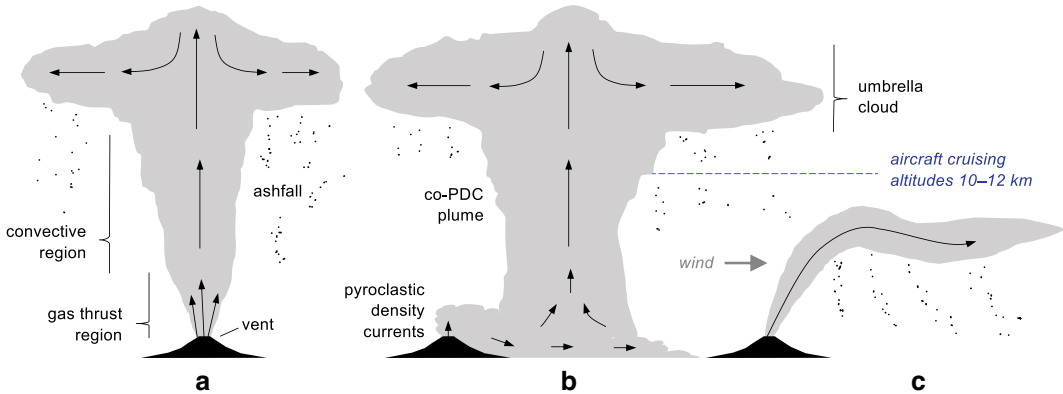


Fig. 2 Sketch of volcanic plumes from different explosive eruption styles and interaction with the background atmosphere. The dynamics of a volcanic plume influence ash dispersal patterns and electrical activity. (a) Sustained, vent-derived plumes are characterized by a momentum-driven gas-thrust region that transitions to a convective region as the column becomes buoyant. (b) Plumes rising purely by convection from ground-hugging

pyroclastic density currents (PDCs) are known as co-PDC plumes. Both (a) and (b) are examples of strong plumes because they rise faster than the background wind speed and may spread out as umbrella clouds. In contrast, weak plumes or wind-dominated (c) are bent over by the wind. Vertical plume heights are for illustration purposes only and may be much higher or lower depending on eruptive and environmental conditions

2020). A well-known example occurred during the 1991 eruption of Pinatubo in the Philippines, which produced an umbrella cloud >1,000 km in diameter (Koyaguchi and Tokuno 1993; Holasek et al. 1996).

Unlike this extreme end member, the most common volcanic plumes arise from low-intensity eruptions that occur daily worldwide. In many cases these plumes do not rise significantly faster than the background wind field, creating a bent-over shape known as a weak or wind-dominated plume (Fig. 2c; Bonadonna et al. 2005; Dürig et al. 2023). A notable example is the 2010 eruption of Eyjafjallajökull in Iceland (Woodhouse et al. 2013). Despite its low to moderate intensity, strong winds transported the ash directly toward Europe and shut down international airspace for nearly a week (Webster et al. 2012; Guffanti and Tupper 2015).

Some volcanic plumes do not rise directly from a central vent. A range of eruptive processes, including dome collapse and volcanic plume instability, may produce pyroclastic density currents (PDCs) that travel along the ground (Wilson and Houghton 2000; Dufek et al. 2015). As these currents entrain air and lose their particle load to sedimentation, they can become

buoyant and loft a plume of preferentially finer ash that rises convectively over a wide area (Fig. 2b, Engwell et al. 2016). During the 1980 eruption of Mount St. Helens in Washington, USA, the co-PDC plume from the lateral blast rose twice as high as the vent-derived eruption columns (Mastin et al. 2023). Recognizing this style of activity is important for eruption monitoring because it indicates (1) the presence of PDCs, which are destructive to nearby communities, and (2) the airborne cloud is more likely to contain fine ash, which affects atmospheric transport and residence times (Engwell and Eychenne 2016).

Water also plays a vital role in governing eruption style and plume dynamics. All volcanic plumes contain some water from the magma itself, which contains 2–7 wt% H_2O . An eruption driven purely by magmatic volatiles is known as a ‘dry’ or magmatic eruption (Houghton et al. 2015, Fig. 3a–b). Additional, external water may be incorporated during magma ascent, eruption into the surrounding environment, and rise of a volcanic plume in the atmosphere. The source, timing, and abundance of this external water impacts a volcanic plume in distinct ways. For example, explosive

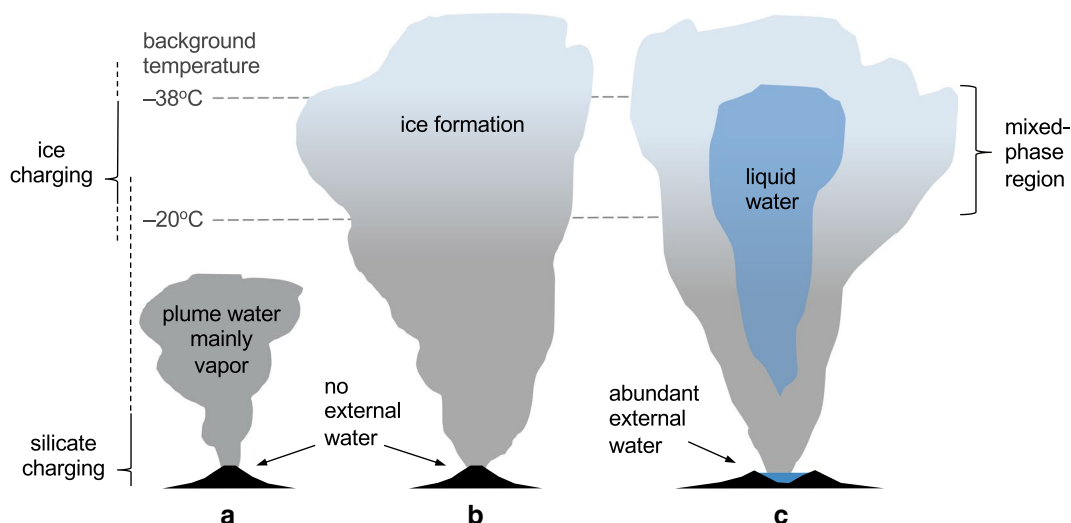


Fig. 3 Simplified sketch of microphysical zones and charging processes in different types of volcanic plumes. Labels on the left indicate electrical charging processes dominated by silicate charging from ash particle interactions versus ice charging related to frozen hydrometeors. Color gradients show dominant water phases: grey indicates vapor with or without minor amounts of condensed water; light blue indicates ice; dark blue indicates significant concentrations of liquid water ($>1 \text{ g/cm}^3$). (a) ‘Dry’ eruptions from low plumes that do not rise above the atmospheric freezing level tend to transport water primarily as vapor with minor amounts of condensed liquid. (b) Larger dry eruption plumes develop ice and

ice-coated ash at temperatures cooler than approximately -20°C . In contrast, large-scale wet eruptions arising from magma-water interaction (c) carry significantly more water and are capable of condensing high concentrations of liquid water in the core updraft; these processes create a mixed-phase region of liquid water, ice, and graupel (soft hail) known to trigger extreme lightning flash rates. Ash plumes sustained well above the freezing level of the background atmosphere (approximately colder than -20°C) produce lightning that is detectable by long-range lightning location systems; plumes below this height create lightning that is only sparsely detectable on a global scale. Figure modified from Van Eaton et al. (2022a, b)

eruption plumes will entrain more water from humid, tropical atmospheres than dry atmospheres (Woods 1993; Glaze and Baloga 1996; Glaze et al. 1997). This added moisture may increase the plume height due to release of latent heat (Graf et al. 1999), but the effect is only pronounced for lower-intensity eruptions. For larger eruptions (mass eruption rates $>1 \times 10^6 \text{ kg s}^{-1}$), the entrained atmospheric water is insignificant relative to the amount of magmatic water already in the plume (Sparks et al. 1997).

Likewise, vaporization of a large water body can overwhelm all other sources and transform the microphysical structure of the resulting plume (Koyaguchi and Woods 1996; Van Eaton et al. 2012). These ‘wet’ (phreatomagmatic) eruptions occur when the eruptive mixture mingles with a body of water such as an ocean, lake, glacier, or hydrothermal system (Fig. 3c). A

well-documented example is the 2009 eruption of Redoubt Volcano in Alaska, which melted and vaporized glacial ice and snowpack (Wallace et al. 2013; Van Eaton et al. 2015). Such plumes carry substantially more water than their ‘dry’ counterparts, producing a zone of liquid water in the warmer core of the plume that may be sustained into the upper troposphere or stratosphere (Van Eaton et al. 2012; 2020). This process creates a mixed phase microphysical region where volcanic ash, liquid water, ice crystals, and graupel (soft hail) undergo electrifying collisions similar to severe thunderstorms (e.g., Saunders 1993). The ability to recognize a water-rich eruption is important to volcano monitoring because the extra water triggers rapid aggregation and fallout of volcanic ash (Van Eaton et al. 2015), affecting the transport and lifetime of hazardous volcanic clouds (Brown et al. 2012).

2.3 Volcanic Lightning

For detailed background on volcanic plume electrification and lightning, we direct readers to several review articles and references therein (Mather and Harrison 2006; James et al. 2008; McNutt and Thomas 2015; Cimorelli and Genareau 2021; Cimorelli et al. 2022). A volcanic plume can become electrified by two general means: charging of silicate particles through magma fragmentation and ash particle collisions, and ice-based collisional charging for plumes that reach the freezing levels of the atmosphere (Fig. 3). In addition, electrification has been observed where lava enters an ocean (Anderson et al. 1965), and there is evidence that ash-poor plumes can become electrically charged through radioactivity (Nicoll et al. 2019).

Lightning and other forms of electrical activity have been observed throughout a volcanic plume. First, small vent discharges (Thomas et al. 2010) often occur at the onset of explosive eruptions with high initial jet velocities (Smith et al. 2021). Vent discharges occur in a swarm in the gas-thrust region of the eruption column. The duration of time over which vent discharges occur correlates with the duration of ash venting (Behnke et al. 2013). The persistent nature of vent discharges creates a distinctive radio frequency signature called continual radio frequency. Lightning first begins to occur seconds to minutes after the onset of an explosion, often overlapping in time with vent discharges. Initially, lightning is proximal to the vent and relatively small in size (tens to hundreds of meters to several kilometers; Thomas et al. 2010). As an eruption column rises in the atmosphere the size of lightning typically increases (up to tens of kilometers, depending on the size of the plume) and occurs at higher altitudes (Behnke et al. 2013). Lightning has been observed in umbrella clouds (Hargie et al. 2018; Van Eaton et al. 2016, 2022a, b), and in the downwind portions of plumes (Behnke et al. 2013). Thus, lightning and electrical activity can occur throughout the various stages of an

eruption, providing opportunities to track the evolution of a plume and infer changes in eruptive processes.

Volcanic electrical activity is fundamentally the same as thunderstorms: the same physical processes (i.e., streamers and leaders) are responsible for the electrical activity. Note that we use the generalized term electrical activity, however, because not all volcanic electrical activity manifests as full-fledged lightning as described in Sect. 2.1. Furthermore, a volcanic plume can be electrified (i.e., carry a net charge) without ever producing an electrical discharge. In particular, current observational and modeling evidence supports the hypothesis that vent discharges are streamer discharges (Behnke et al. 2018, 2021; Liu and Dwyer 2020), which occur either between pockets of charge in the gas-thrust region or as corona discharges on charged ash particles. Vent discharges are associated with impulsive ejections of ash with high exit velocities (Smith et al. 2021), producing supersonic flows that create rarefied regions of gas (Méndez Harper et al. 2018). It is hypothesized that vent discharges arise as charged ash traverses this low-pressure region and undergoes electrical breakdown due to the reduced dielectric strength of air (Méndez Harper et al. 2018).

Terminology for volcanic lightning is often applied due to where it occurs in the plume. Near-vent lightning, as the name implies, refers to lightning that occurs near to the vent, likely within the gas-thrust region of the eruption column (Thomas et al. 2010). Plume lightning refers to lightning that occurs at higher altitudes, in the buoyant portions of the plume (Thomas et al. 2010). Near-vent lightning is, on average, typically smaller than plume lightning. This is partly due to the volume increase of the eruption column as it grows into a fully developed plume. In addition, the size of turbulent eddies plays a role in controlling the size of charge regions (Bruning and MacGorman 2013), and as the volume of a turbulent volcanic plume increases the length scale of lightning also increases, commensurate with the increase in the characteristic length scale of turbulence (Behnke and Bruning

2015). The terms ‘near-vent lightning’ and ‘plume lightning’ were defined based on observations of lightning from the 2006 eruption of Augustine Volcano (Thomas et al. 2010), where there was an observed gap in time between when lightning occurred proximal to the vent and when it occurred in the drifting plume. However, this temporal cessation of lightning does not always occur, particularly in larger eruptions (e.g., Behnke et al. 2013), making it difficult to discern between the two. We caution future authors to use these terms carefully or not at all, as drawing strict boundaries between these two regimes is difficult, and, beyond the size of the discharges, there is not necessarily a physical difference between plume lightning and near-vent lightning. However, the terms intra-cloud/cloud flash and cloud-to-ground can and should be applied to volcanic lightning because they reflect physical processes; the terms are not mutually exclusive with volcanic lightning terms.

3 Instrumentation for Lightning Detection

Lightning produces electromagnetic radiation and is commonly detected by sensors measuring electric fields, magnetic fields, or optical emissions. Lightning can also be detected acoustically (Johnson et al. 2011; Haney et al. 2018) and through electrical ‘glitches’ induced in the cables of ungrounded seismic and infrasound arrays (McNutt and Davis 2000; Haney et al. 2020). In the absence of lightning, an electrified plume can also be detected by measuring quasi-electrostatic fields, or attenuation of GPS signals (Méndez Harper et al. 2019). Each method of detection has strengths and weaknesses, and when combined improves the analysis of volcanic eruptions. Importantly, each instrument measures different processes from lightning flashes, and how one instrument determines a set of measurements to be a flash may vary from other instruments.

3.1 Ground-Based 2-D Lightning Location Systems

There are multiple observation platforms that monitor lightning using electric field waveforms and magnetic direction finding to pinpoint the latitude and longitude of lightning flashes both globally and regionally (Nag et al. 2015). A few examples of global systems are Vaisala’s Global Lightning Dataset (GLD360; Mallick et al. 2014), Earth Networks Total Lightning Network (ENTLN; Zhu et al. 2022), and the World-Wide Lightning Location Network (WWLLN; Hutchins et al. 2012). Examples of regional networks include ATDNet in Europe (Bennett et al. 2010) and the National Lightning Detection Network in the United States (Cummins and Murphy 2009). Such sensor networks are often referred to as lightning location systems in the literature, though more general usage of that term is often applied as well. In this chapter we use “lightning location system”, or “LLS” to refer to a ground-based sensor network that detects lightning in two dimensions either regionally or globally.

Figure 4 illustrates how these lightning location systems detect electromagnetic radiation to pinpoint the location of a flash. Both very low frequency (VLF; 3–30 kHz) and low frequency (LF; 30–300 kHz) sensors can detect radiation that propagates over the surface of the Earth (ground wave) and radiation that reflects between the ground and the ionosphere (sky wave; Said et al. 2010). However, VLF sensors often have long baselines (i.e., long distances between sensors), on the order of thousands of kilometers, and thus take advantage of the low attenuation of VLF waves propagating in the Earth-ionosphere waveguide. As the radiation waves pass a sensor, waveforms are recorded. Then, using time of arrival (TOA; Said et al. 2010) or time of group arrival (TOGA; Dowden et al. 2008) processing techniques, the source of the radiation is located on Earth’s surface. One disadvantage of the longer baselines is that the sensors are less sensitive to low-amplitude

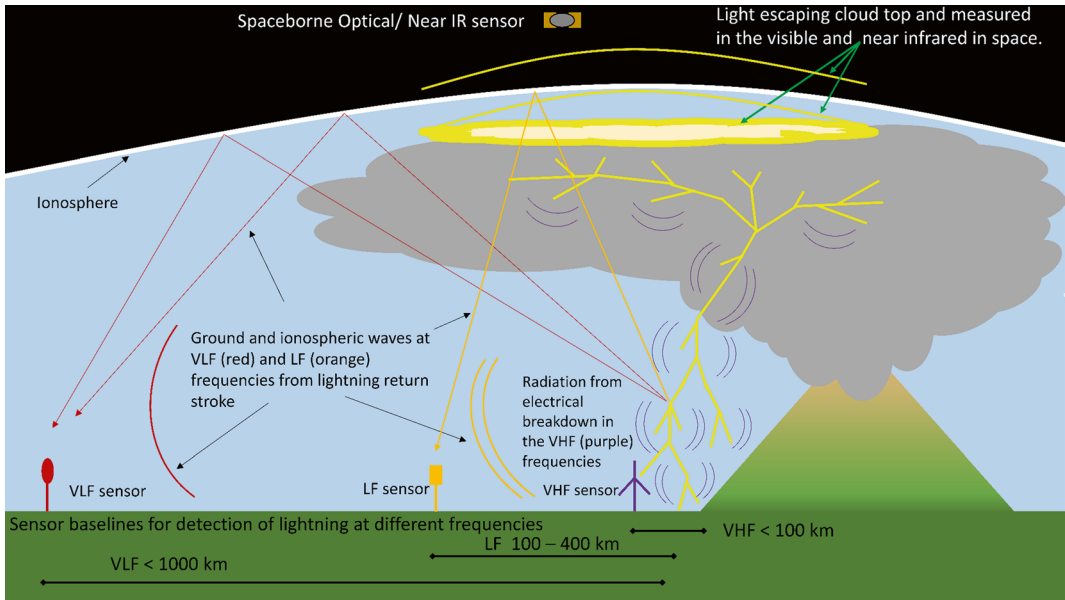


Fig. 4 Illustration of lightning measurement techniques using sensors that operate across the electromagnetic spectrum. VHF sensors, like Lightning Mapping Arrays, detect radiation from the electrical breakdown of air at near ranges (~ 100 km). LF sensors and VLF sensors detect radiation from current pulses produced by return strokes and cloud pulses. Both VLF and LF sensors can detect radiation that propagates directly over the surface

of the Earth, or as a reflected wave within the Earth-ionosphere waveguide. VLF sensors have baselines of thousands of kilometers, while LF sensors typically have baselines on the order of hundreds of kilometers. Optical spaceborne platforms can observe lightning in the visible at night or at any time of day using the near infrared ($777.4 \mu\text{m}$)

current pulses. Thus, VLF systems primarily detect cloud-to-ground return strokes, though large-amplitude cloud pulses can be detected as well. WWLLN and GLD360 are examples of VLF sensor systems.

LF sensors typically operate between 30–300 kHz, but in practice often have some overlap with the VLF ranges and/or frequencies above LF. For example, the NLDN operates in a range between 1–350 kHz, while ENTLN operates between 2 kHz and 12 MHz. LF sensors often use both TOA and magnetic direction-finding techniques (Cummins and Murphy 2009) to locate the radiation sources. The baselines of these sensors are on the order of 150–400 km, allowing for a higher sensitivity to smaller amplitude pulses. Thus, these sensors are sensitive enough to detect both cloud pulses and return strokes.

The strength of these systems is the capability to pinpoint the location of return strokes in cloud-to-ground (CG) lightning flashes and

some cloud pulses. They can also estimate polarity and peak current of lightning pulses, which aid in the classification of the charge structure of the plume and near-vent lightning. The main weaknesses of these observations relate to the spatial structure of lightning. Because LLS measurements are strictly point data locations, spatial mapping of the lightning extent is challenging.

3.2 Ground-Based 3-D Lightning Mapping Systems

One of the primary instruments used for three-dimensional mapping of lightning is the Lightning Mapping Array (LMA; Rison et al. 1999). LMA sensors observe radiation emitted during the process of electrical breakdown by lightning leaders as they propagate through the air (Fig. 4). The typical frequency range the

LMA operates within a 6 MHz band between 60–90 MHz. The detection range of an LMA is dependent on configurations of sensors and is mostly limited to a couple hundred kilometers (Thomas et al. 2004; Chmielewski and Bruning 2016). The data are post-processed using TOA method to give 3-D locations. Near real-time data processing is possible (c.f. Goodman et al. 2005), enabling the capability to establish alerts with the data. In this case the data are often decimated for ease of transmission and faster processing. The typical latency for real-time processing is 2–4 min. The advantages of LMA observations are the three-dimensional structure of lightning flashes with the cloud, the ability to discern the cloud's charge structure, and high detection efficiency (>99%) of discharge processes. The main weaknesses of these measurements are the limited range and complexity of deployment to active volcanic regions.

3.3 Satellite-Based Lightning Detection

Multiple platforms exist in space to measure properties of lightning that can emanate from volcanic eruptions. Most are in low-Earth orbit and require the satellite to pass over an event at the right time, while others are positioned in geostationary orbit and continuously monitor a defined field of view.

In particular, there are a number of optical lightning mappers that are in orbit which are useful in volcanic monitoring and scientific research (Fig. 4). Optical lightning mappers detect emissions from atomic oxygen at 777.4 nm to monitor lightning activity during the day and at night from space (Christian and Goodman 1987; Christian et al. 1989). These instruments are present at both low-earth orbit (Tropical Rainfall Measuring Mission Lightning Imaging Sensor (TRIMM-LIS), Buechler et al. 2014; International Space Station Lightning Imaging Sensor (ISS-LIS), Blakeslee et al. 2020) or at geostationary orbits (GOES-R Geostationary Lightning Mapper (GLM), Rudlosky et al. 2019; Meteosat Third

Generation Lightning Imager (MTG-LI)). The advantages of these types of observations include the characterization of spatial extent and optical brightness of lightning discharges. The flash extent indicates where active charging is ongoing, which can be correlated to ground discharge and cloud pulse locations from other sensors like GLD360 or ENTLN. The main weakness is that the detection efficiency depends on the height of the lightning flash and the opacity of the cloud, because light can be absorbed or scattered by airborne particles and water phases, changing its ability to escape the cloud top and reach the satellite. For volcanic plumes, the effects of these scattering properties are even more poorly constrained than they are for meteorological storms.

3.4 Combining Lightning Datasets for Maximum Utility in Volcanic Monitoring

Use of a lightning detection system in isolation can limit observational insights due to the weaknesses of the different approaches described above. The atmospheric electricity community advocates for a data fusion approach for any analysis of lightning (e.g., Schultz et al. 2018, 2021). The primary need for fusion is between systems that pinpoint return strokes or cloud pulses and those that map lightning in two or three dimensions. Figure 5 illustrates the importance of combining these approaches. ENTLN flash locations are presented for a 1 s interval during an eruption of Sangay Volcano, Ecuador. Note that ENTLN observed one negative CG and one positive CG during this time period at two different locations. Spatial lightning data from GLM during this same time interval reveals that both ENTLN pulses are part of the same lightning flash. This combination of data provides more detail about the lightning within the volcanic plume, which in this case shows that the two ENTLN pulses are likely part of the same flash.

There will naturally be parallax between the ground-based and space-based observations

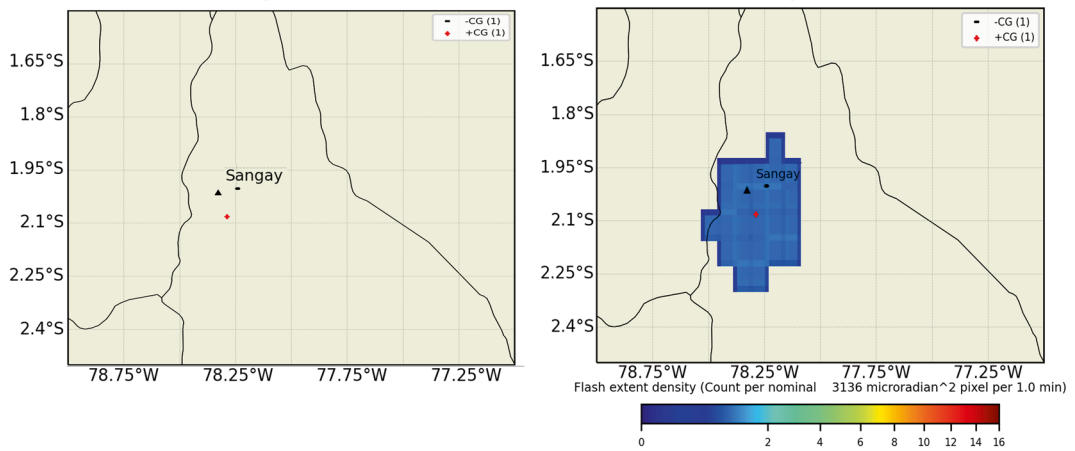


Fig. 5 An intercomparison of a single lightning location system (a) and (b) a fused lightning location system/GLM observation for the same lightning event on 11 March 2021 at 07:45:03 UTC over Sangay Volcano in Ecuador. ENTLN pulses are shown as black negative

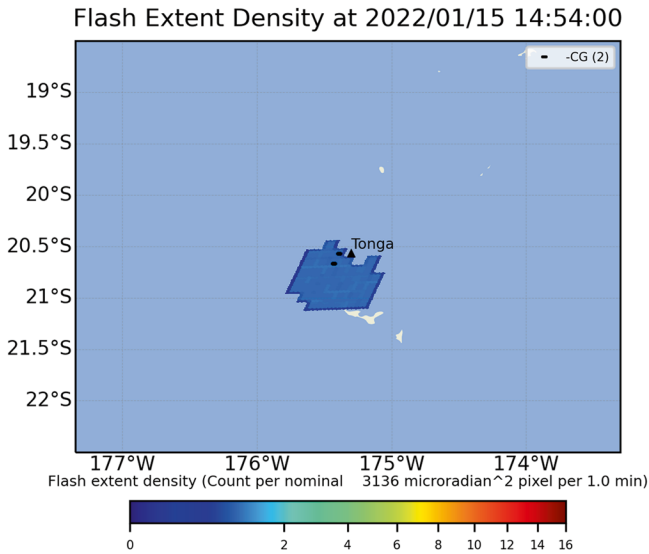
signs (negative CG) and red plus signs (positive CG). The black triangle shows the approximate location of the volcano. Blue shading in (b) indicates the locations where light was observed by GLM from this lightning flash

of lightning because systems like ENTLN are geolocated to the Earth’s surface while observations like GLM are geolocated to the cloud top some distance above the ground. Figure 6 shows an example of a GLM flash footprint offset several kilometers southwest of a corresponding ENTLN CG pulse during the eruption of Hunga Volcano on 15 January 2022 (Briggs et al. 2022; Van Eaton et al. 2023).

3.5 Electric Field Mill and Field Change Sensors

Electric field mills (EFMs) are used to measure the ambient electric field within earth’s atmosphere and the quasi-static electric fields produced by charged clouds. Static electric fields are always present, even in fair weather, due to the potential gradient between the earth and the

Fig. 6 Overlay of a single lightning flash at 14:27:08 UTC during the Hunga Volcano eruption on 15 January 2022 highlighting the potential for parallax at large view angles between space-based and ground-based lightning sensors. Black negative signs indicate negative CG pulses identified by ENTLN, and the black triangle shows the approximate location of Hunga Volcano. Blue shading indicates the locations where light was observed by GLM



ionosphere. The electric field measured at the ground depends on the quantity and arrangement of charge in a cloud, thus a single measurement with an EFM can only reveal the net charge in a cloud. With several sensors, one can use EFM measurements to estimate the structure of the charge within a cloud or plume (e.g., Miura et al. 2002). An EFM can also detect lightning, but due to its sampling rate is only able to measure the total electric field change for an entire lightning flash. The typical frequency bandwidth of EFMs is on the order of 10 Hz or less.

Electric field change sensors operate at higher frequencies than EFMs and are used to study lightning physics. The specific frequency range used varies among sensor types and affects the types of lightning processes that are resolved. However, the basic principle of the sensor is to detect changes in electric fields produced by the movement of charge within a lightning flash. With a field change sensor, one can derive the total charge transferred per flash and per pulse, and by using an array of sensors, one can determine the three-dimensional source locations of pulses observed during individual lightning flashes. Field change measurements can be combined with LMA and GLM type measurements to provide more insight into flash processes (e.g., Bitzer et al. 2013, 2016, Fairman and Bitzer 2022; Haley et al. 2021).

3.6 Data Availability

For real-time visualization, datasets like WWLLN, Blitzortung (https://www.blitzortung.org/en/live_lightning_maps.php), GLM, and ISS-LIS are readily available to view online. They can provide quick insight into current activity at a given location. Datasets like GLD360 and ENTLN require agreements to be in place for real-time uses and must go through the parent companies. Most of the same datasets are also available for non-real-time, post processing analysis, which may require additional processing to exploit the data set.

4 Lightning in Volcano Monitoring

Observations of lightning and electrification can be used both for eruption detection and characterization. Though volcanic lightning is a relatively young field, researchers have already shown a wide range of applications for lightning data to gain insight in volcanic eruptions. In this section, we cover how lightning has been used in volcano monitoring contexts.

4.1 Eruption Detection

The most fundamental way to use lightning observations or related measurements for volcano monitoring is to detect that an explosive eruption has occurred or is underway. There are several methods to employ for eruption detection; the choice of methodology may depend on the level of insight needed into an eruption and the practicality of the method for a specific monitoring situation. We divide these methods into two categories: methods for detecting an electrified plume and methods for detecting lightning. Both types of methodology can help determine if an eruption has occurred.

4.1.1 Detection of Electrified Plumes

The presence of charge in a plume can be detected through measurement of quasi-static electric fields with an electric field mill or similar sensor (Sect. 3.5). The net electric field detected by a single sensor will signify that a charged plume is nearby, and the field will vary with time depending on the changes in the quantity or density of charge (e.g., Haley et al. 2021), the organization of charge (e.g., Lane and Gilbert 1992), the location and movement of the plume in relation to the sensor (e.g., Miura et al. 2002), and the occurrence of lightning (e.g., Haley et al. 2021). Multiple sensors can be employed to constrain the overall charge structure (Miura et al. 2002). Charged plumes can also be detected with GPS/GNSS receivers due to the attenuation of L-band radio signals caused

by interaction with charged particles in a plume (Mendez Harper et al. 2019).

Some advantages of the measurement of quasi-static fields are that the sensors are relatively inexpensive and simple to deploy. Data volume is also low due to the low sampling rates of electric field mills. This method allows for one to detect an electrified plume that may never produce lightning. However, the sensors need to be relatively close to a volcano (less than 10 or 20 km is typical) to detect a charged plume.

4.1.2 Detection of Lightning

Detection of lightning from electrified plumes can be achieved with many different types of sensors, as described in Sect. 3. There are notable differences in the types of volcanic lightning that can be detected based on the instrumentation used and its proximity to a volcano. Proximal sensors—regardless of frequency range used—will be able to detect more lightning than global lightning detection networks due to increased sensitivity. However, the frequency range of the sensor has implications for the types of volcanic lightning that can be detected (Behnke and McNutt 2014). Generally, sensors operating at medium frequency and lower detect electric or magnetic fields produced by current pulses along conducting leader channels (i.e., return strokes and cloud pulses). Electromagnetic radiation is also produced by the process of electrical breakdown of air, which accelerates charge; this process occurs during the formation of streamers and leaders. This type of electromagnetic signal is detectable at very high frequency. Thus, vent discharges are generally only detectable with sensors that detect in VHF, while near-vent lightning and plume lightning are frequency-independent, though proximal measurements would be needed to detect weaker lightning, including most near-vent lightning and some plume lightning.

Currently, there are several lightning detection networks in use for volcano monitoring operationally. One example is the WWLLN Global Volcanic Lightning Monitor, which was created through partnership between the

University of Washington, USA, and the U.S. Geological Survey (Ewert et al. 2010). WWLLN tracks lightning detected within 20 and 100 km of all active volcanoes in the Smithsonian Global Volcanism Program database. The data are available in near real-time on their webpage <http://wwlln.net/USGS/Global/>. WWLLN applies a spatial algorithm to identify lightning that may be associated with an eruption rather than a passing storm. Specifically, if there is more lightning detected within 20 km of a volcano than within 100 km, an email is sent to those who have requested alerts for that region of the world. This simple algorithm results in many false positives, especially for places like Indonesia and the Philippines where lightning storms occur almost daily near active volcanoes. However, it is possible for individual volcano observatories to fine-tune the alerts using knowledge of local weather patterns and integrating with other volcano monitoring data (see Sect. 5.2).

Algorithms for eruption detection have also been developed for use with lightning detection instruments that are local to a volcano. For example, Vossen et al. (2021) used lightning detectors sensitive to 1–45 Hz to monitor electrical activity during recurring (July 2018–January 2020) small-scale explosions from the Minamidake crater of Sakurajima volcano in Japan. The sensors are prototypes of a Biral Thunderstorm Detector BTD-2000, which detect slowly changing electric fields using two antennas of differing sensitivity. Vossen et al. (2021) created an algorithm that looks for transient signals of the same polarity on both antennas simultaneously. If the transient exceeds a specified signal-to-noise ratio, the transient is considered an electrical discharge. The performance of the algorithm was determined by applying the algorithm to a catalog of manually identified time periods with and without explosive activity. Vossen et al. (2021) found that the algorithm made an accurate determination of the presence or absence of electrical activity in 73% of cases examined.

By contrast, Behnke et al. (2022) demonstrated a proof-of-concept eruption detection

algorithm using measurements of very high frequency (VHF, 30–300 MHz) radiation from volcanic electrical activity. The proposed algorithm is based on machine learning algorithms that can distinguish between VHF radiation impulses from vent discharges and lightning. The algorithm would exploit the characteristic pattern of electrical activity commonly observed during explosive volcanic eruptions: A burst of vent discharges followed by a period of lightning flashes. The algorithm would determine if an eruption has occurred by first looking for an increase in the rate of detected radiation impulses above the background noise level. Then, the algorithm would examine the classification of the detected radiation impulses using the machine learning model and declare that an eruption had occurred if the impulses were first classified as being majority vent discharges and then switched to being majority lightning after some specified time interval. The specific parameters of the algorithm (i.e., the durations of vent discharges and lightning and the time gap between vent discharges and lightning) would be tunable depending on the expected eruption size. In the example given by Behnke et al. (2022), the identification of an eruption by the algorithm would occur <10 s after the first detection of electrical activity, and we speculate that it may take longer (up to a minute) for more energetic eruptions, where vent discharges occur for longer durations. The machine learning model employed by this proposed eruption detection algorithm to determine if a given radiation event is part of a period of vent discharges or a lightning flash had an accuracy of 97.7%. The eruption detection algorithm itself was not evaluated for performance, as there was insufficient data acquired to robustly demonstrate algorithm performance.

4.2 Eruption Characterization

Measurements of lightning can also provide insights into volcanic processes and the eruption source parameters (Mastin et al. 2009; Aubry et al. 2021) needed for ash dispersal forecasting

(Table 2). In the following section we highlight case studies from the existing literature that show promising relationships between lightning data and parameters such as vent location, eruption duration, and plume composition, height, morphology, and trajectory.

4.2.1 Vent Location

In regions with many closely spaced volcanoes, or volcanoes with more than one historically active vent, it may not be immediately obvious where a volcanic plume is coming from at the earliest stages of detection. The specific volcano or vent locations may have implications for eruption dynamics and hazards—for example, whether the vent is underneath a glacier or other body of water may influence eruption style, plume microphysical structure, and charging processes (Fig. 3). Lightning monitoring can help identify the vent location in near-real time. There have been several closely monitored eruptions during which an LMA located vent discharges in a plume directly within and above the volcanic crater, with location accuracies of tens to hundreds of meters (Behnke et al. 2013, 2014, 2018).

For more remote volcanoes with fewer in situ sensors, longer-range methods become important. Arason et al. (2013) describe a method to use data from 2-D lightning location systems to estimate the volcanic vent position by assuming that lightning locations either occurred close to the vent or moved away from the volcano in the downwind plume over time. Using this method, the Icelandic Meteorological Office used near real-time ATDnet lightning locations to provide vent location estimates using a wind correction from weather forecast data. On a larger scale, it can be relatively straight forward to use globally detected lightning to identify the volcanic source because the lightning tends to concentrate within 20–30 km of the volcanic source (Van Eaton et al. 2020) rather than moving through the broader region like a typical thunderstorm. Despite uncertainties of several kilometers for long-range lightning locations, this method can help narrow down potential vent sites at the earliest stages of eruption (Arason et al. 2013).

Table 2 Selected examples of eruption source parameters and plume dynamics inferred from electrical measurements in the published literature. These examples are selected to highlight the strengths and weaknesses of different approaches, but are by no means exhaustive. Local monitoring uses sensors on or near the volcanic edifice, including LMA, photography, field mills, and electric field change sensors. Remote monitoring uses long-range sensors, including ground-based 2D lightning location systems and satellite-based optical sensors

Volcanic process or feature	Local measurements	Remote measurements
Location of active vent	An LMA with 5+ stations can map lightning in three dimensions, including discharges originating directly from the source of the volcanic plume (Thomas et al. 2010)	Long-range lightning location systems have been used to identify the eruptive vent by tracking lightning through time and correcting for wind speed and direction (Arason et al. 2013)
Eruption onset	The onset time of high-velocity, impulsive volcanic plumes may be detected by the onset time of vent discharges (Behnke et al. 2018; Smith et al. 2021) or voltage changes detected by an electric field change sensor (Vossen et al. 2022)	Globally detected lightning within 20 km of the volcano provides an indication of when an ash plume has risen well above the local atmospheric freezing level (Arason et al. 2011; Van Eaton et al. 2020)
Eruption duration	The duration of charged ash emissions may be estimated from the duration vent discharges (Behnke et al. 2013) or other near-source electric field measurements (Vossen et al. 2022)	Globally or regionally detected lightning tend to only provides the duration of plumes sustained above the local freezing level (Van Eaton et al. 2016, 2020)
Plume height	The maximum altitude of LMA-detected lightning provides a minimum height for the plume (Woodhouse and Behnke 2014), and the number of discharges may correlate with plume height (Vossen et al. 2021)	The maximum height of high-altitude plumes may be estimated from flash rates using empirical relationships (Prata et al. 2020; Van Eaton et al. 2022a, b)
Umbrella cloud growth	No published examples yet	A roughly circular arrangement of 2-D lightning locations expands with the radially expanding umbrella cloud (Van Eaton et al. 2022a, b; Smith et al. 2022)
Gas-thrust (jet) versus convective regions	Vent discharges detected by LMA appear to originate in the volcanic jet and may constrain its dimensions (Behnke et al. 2018); High-speed video analysis also shows lightning flashes concentrated in the jet region (Cimarelli et al. 2016)	The current working assumption is that globally networks only readily detect lightning in the upper, convective regions of volcanic plumes (Van Eaton et al. 2020)
Turbulence characteristics	LMA-detected flash energy spectra have shown changes in the plume's characteristic turbulent length scale over time (Behnke and Bruning 2015)	Satellite-based optical measurements have shown the largest flashes developing >30 km from the volcano, implying a more stratified ash cloud at those distances (Schultz et al. 2020)
Generation of pyroclastic density currents (PDCs)	An abrupt change in the signature of near-source electric field measurements at Stromboli have coincided with development of PDC (Vossen et al. 2022)	Secondary increases in lightning rates have been associated with PDCs using ground-based LLS (Van Eaton et al. 2016) and satellite-based optical measurements (Schultz et al. 2020)

(continued)

Table 2 (continued)

Volcanic process or feature	Local measurements	Remote measurements
Mixed-phase microphysics (coexisting liquid water and ice in the plume)	Extremely high rates of LMA-detected lightning have been associated with a mixed-phase microphysical region in volcanic plumes (Behnke et al. 2013). Local photographs have been used to infer ice formation at the base of an umbrella cloud (Van Eaton et al. 2022a, b)	Volcanic plumes observations have consistently shown an association between ice formation and the onset of globally detected lightning (many studies, including Cahalan et al. 2023)
Amount of magma-water interaction	No published examples yet	Despite theoretical analyses suggesting a link between magma-water interaction and plume microphysical structure, observations of wet and dry plumes from the same eruption have not yet shown convincing differences in the amount of globally detected lightning (Van Eaton et al. 2020)
Plume charge structure	LMA-detected lightning has provided detailed information on the charge structure of volcanic plumes (Behnke et al. 2014). Electric field mills can reveal net charge distribution within a plume (Miura et al. 2002)	Polarities of globally detected lightning provide some information on the net charge carried by the plume (Schultz et al., 2020)
Charge characteristics of volcanic particles	Electric charge can be measured from actively falling particles if sensors are positioned within the fallout zone (Gilbert et al. 1991; Pollastri et al. 2022)	No published examples yet
Modification of volcanic particles due to lightning	Samples of volcanic ash have been found to contain lightning-induced volcanic spherules, which provide textural evidence of lightning in the plume (Genareau et al. 2015)	No published examples yet

4.2.2 Eruption Onset and Duration

Poor visibility and wind noise can obscure satellite, webcam, and acoustic methods used to determine both the onset of an explosive eruption and whether the emissions are currently ongoing. These issues are more pronounced for remote volcanoes and small plumes that do not rise above the meteorological cloud deck. However, large eruptions can also form ash clouds that obscure views of activity closer to the vent. In these cases, there is potential for lightning data to assist. LMA observations during the 2009 eruption of Redoubt Volcano in Alaska revealed that bursts in located radio frequency sources occurred concurrently with explosive activity (Behnke et al. 2013). These bursts were determined to be primarily from vent discharges, which suggests that by measuring vent discharges, one may be able to estimate the onset and duration of an explosive event (Behnke et al. 2022). Near-source observations of electrostatic field changes using a modified Biral Thunderstorm Detector were also able to detect the onset and duration of some small-scale explosions at Stromboli volcano in Italy (Vossen et al. 2022). Likewise, remote

measurements from ground-based LLS can help define eruptive onset and duration (Van Eaton et al. 2016; 2020, 2022). However, the lower sensitivity of these methods mean they only tend to detect lightning when volcanic plumes are sustained well above the local freezing level (Arason et al. 2011), which may range anywhere from sea level to 10 km or higher depending on the site and season.

4.2.3 Plume Height

Plume height is one of the most important parameters needed for ash dispersal forecasting because it constrains both the mass eruption rate and injection height of volcanic ash into the atmosphere (Mastin et al. 2009). Linking electrical activity to plume height is an active area of research, but the initial studies are promising. Across a variety of studies and instrumentation methods, results show that taller plumes (i.e., higher eruption rates) tend to produce more lightning (Fig. 7). This metric can provide qualitative, near-real-time insights into whether an eruption is intensifying or waning. For example, LMA observations from the 2009 eruption of Redoubt Volcano showed a relationship

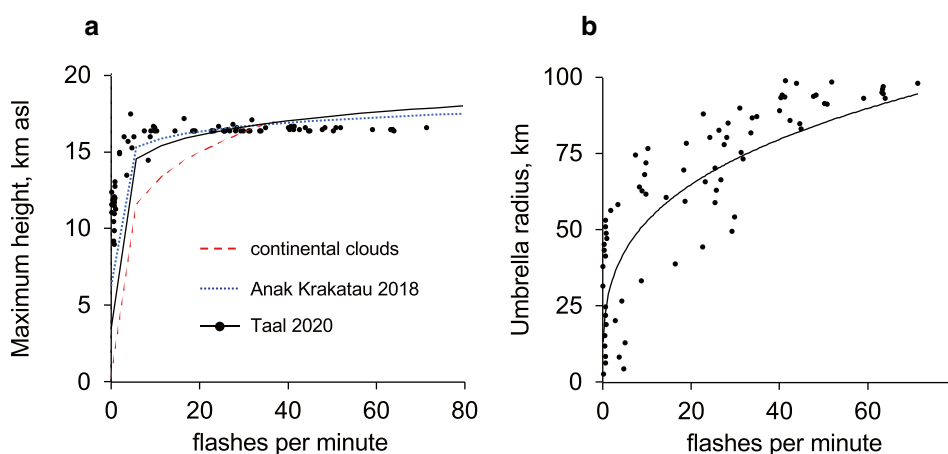


Fig. 7 Empirical relationships between lightning rate, volcanic plume height (ASL), and umbrella cloud radius. (a) There is a power-law relationship between maximum plume heights and flash rates of globally detected lightning from the 2018 eruption of Anak Krakatau, Indonesia (Prata et al. 2020; blue dotted line) and 2020 eruption of Taal Volcano, Philippines (Van Eaton et al. 2022a, b;

black line). The data from these two eruptions overlap within uncertainty, but have a distinct trend compared to the non-volcanic thunderstorms examined by Price and Rind (1992) (continental clouds; red dashed line). (b) Lightning rates from the Taal eruption also show a power-law relationship with the size of the growing umbrella cloud. Figure modified from Van Eaton et al. (2022a, b)

between maximum plume height and the total number of VHF sources detected (Behnke et al. 2013). Redoubt's explosive events with plume heights <10 km above sea level (ASL) produced far fewer LMA sources than those >10 km. Studies at other volcanoes using near-source sensors have examined the positive relationship between electrical activity and plume height for much smaller eruptions, including at Sakurajima, Japan (Smith et al. 2021) and Stromboli, Italy (Vossen et al. 2022). However, these campaign-style deployments vary greatly in detection efficiency due to the different instrumentation and array geometries used. As a result, there are not yet any lightning-plume height relationships that can be applied to different volcanoes using near-source sensors.

In contrast, the relatively stable configuration of global lightning networks over the past ~5 years has enabled some recent comparisons across different volcanoes. The eruptions of Anak Krakatau, Indonesia, in 2018 and Taal Volcano, Philippines, in 2020 both showed a strong relationship between lightning flash rates and maximum plume heights over time (Fig. 7a), described by

$$H = 12.69 F^{0.08} \quad (1)$$

where H is the maximum plume height in kilometers and F is flashes per minute ($R^2 = 0.76$).

The Taal eruption also showed that lightning rates increased with umbrella cloud growth (Fig. 7b). However, it remains to be seen how these empirical relationships evolve as more data is gathered on different eruption styles and as updates to the long-range networks change their detection efficiencies from one region to the next.

4.2.4 Plume Morphology and Trajectory

In some cases, the morphology and transport direction of a volcanic plume may be constrained by its lightning characteristics. The presence of an expanding, circular region of lightning is a good indicator of an umbrella cloud, suggesting a strong plume from a high-intensity eruption (Figs. 2 and 8a), whereas a narrower band of lightning locations moving

away from a point of origin suggests a weak plume bent over by the wind (Figs. 2, 8b). A study of the 2019 eruption of Raikoke Volcano in Russia's Kuril Islands showed that 2-D lightning locations from GLD360 tracked different portions of the downwind plumes, providing a means to identify the atmospheric trajectory of ash at different altitudes (Smith et al. 2022). One caveat to bear in mind is that network geometry issues can lead to an apparent elongation of the 2-D locations, so it is wise to find out in advance if such a bias exists within the region.

5 Integrating Lightning into Volcano Monitoring

Incorporating volcanic electrical measurements into a monitoring framework can take many different paths, involving varying levels of expertise and complexity. Here we describe three tiers of complexity for using lightning data in volcano monitoring.

5.1 Tier 1: Tap into Existing Lightning Detection Networks

The simplest option for electrical monitoring is to tap into existing ground-based 2-D lightning location networks (Sect. 3.1). This approach has the fewest barriers to entry because it does not require direct involvement in instrument installation, maintenance, or data telemetry and processing. Yet, a subscription to near real-time data from one or more of these networks—some of which are low or no cost—can help address whether a volcano of interest is producing a high-altitude volcanic plume (Table 2).

An example of this approach is the response to the 2016–2017 eruption of Bogoslof Volcano in Alaska. Bogoslof is a shallow submarine volcano in the Bering Sea of Alaska, with the nearest monitoring sensors ~50 km away on neighboring Okmok Volcano. During the eruption response, the Alaska Volcano Observatory downloaded lightning data directly from the WLLN website every minute and sent

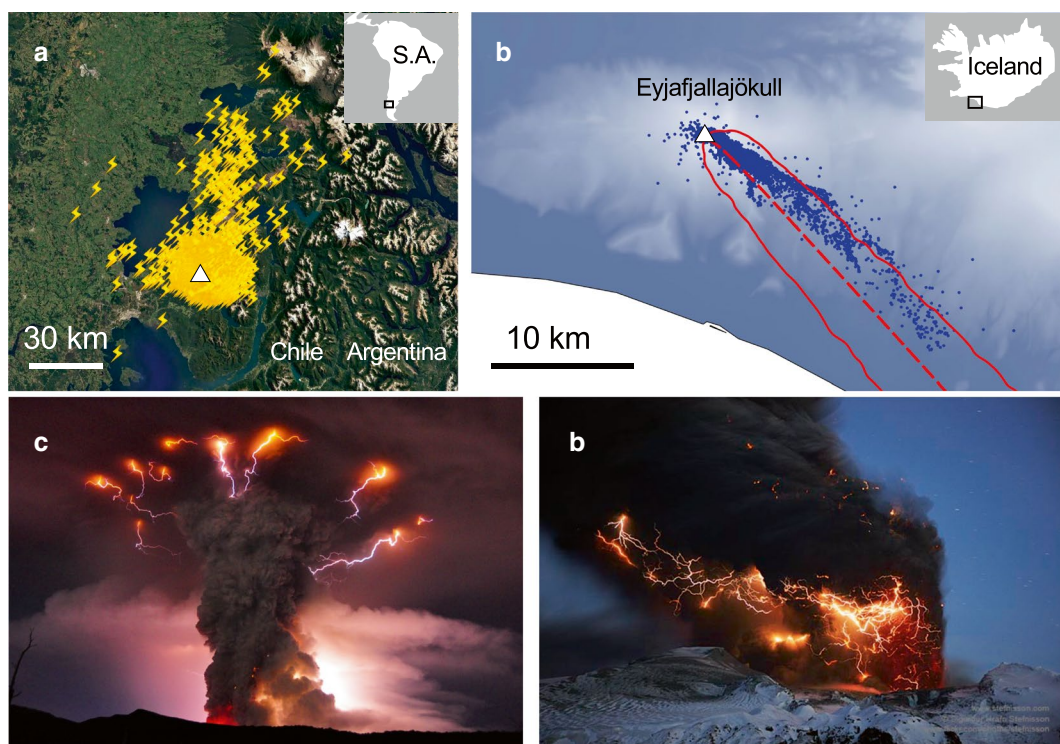


Fig. 8 Examples of lightning revealing the morphology of a volcanic plume. (a) The 23 April 2015 eruption of Calbuco volcano in Chile produced an umbrella cloud, highlighted by the broadly circular arrangement of WWLLN-detected lightning, followed by an alignment of lightning following the high-altitude cloud downwind; modified from Van Eaton et al. (2016). (b) The 11 May 2010 eruption of Eyjafjallajökull in Iceland produced a weak, wind-dominated plume; LMA-detected lightning (blue dots show the VHF sources) tracked the modeled

plume trajectory (red lines); image modified from Woodhouse and Behnke (2014). Photographs show lightning from the eruptions of (c) Puyehue-Cordón Caulle, Chile, on 5 June 2011, taken by Daniel A. Basualto Alarcón using a 30-s exposure time (Basualto et al. 2023), and (d) Eyjafjallajökull in Iceland on 17 April 2010, during the phreatomagmatic phase of the eruption characterized by magma interaction with glacial water, taken by Sigurdur Stefánsson using a 15-s exposure time. Photos reprinted with permission

alerts to the response team by text message when lightning was detected in the vicinity of Bogoslof (Coombs et al. 2018). Due to the rare occurrence of background thunderstorms in the Aleutian Islands, any lightning near the volcano had a high likelihood of being associated with an eruption. At the time, operational use of this data was qualitative, providing situational awareness that there may be high-altitude volcanic ash impacting aircraft cruising levels, which triggered a cross-check of other

monitoring data to confirm the eruptive activity. However, there was one notable case of an explosive event detected in real-time using WWLLN lightning alone due to complications with the seismic and infrasound data (Coombs et al. 2018). Post-analysis confirmed that 32 out of the 70 explosive events created globally detectable lightning over the eight-month eruption, and there were four instances in which lightning provided the earliest detectable signal (Van Eaton et al. 2020).

5.2 Tier 2: Tailor Volcano-Specific Alerts

Fine-tuning existing lightning data for a specific volcano or region can add value to monitoring efforts without direct investment in new instrumentation. For example, it is possible to work with network providers to develop a more sensitive detection algorithm for an area of interest. Lapiere et al. (2018) showed that using two sensors to locate lightning, rather than the usual 3 or more, can increase detection sensitivity by reporting lightning that would have otherwise been filtered out. In some cases, this process improves eruption detection times by several minutes by capturing the smaller, weaker lightning that occurs earlier in a volcanic eruption (Van Eaton et al. 2020). However, it does result in more spurious detections caused by radio frequency interference from the environment. This approach works best when the pros of more sensitive detection outweigh the cons of noisier data, such as when a higher threat volcano shows signs of unrest.

Another way to fine-tune lightning data for a specific region is to apply spatial and temporal filters to distinguish volcanic lightning from background thunderstorms. An example is the algorithm of Baissac et al. (2021), who filtered incoming WLLN-detected lightning data to improve their monitoring of active volcanoes in Chile and Argentina. Their method established three levels of alerts (green, yellow, and red) based on relative amounts of lightning within 20 km and 100 km of each volcano. The red alert is triggered when there is either: (a) lightning within 20 km only; or (b) at least twice as much lightning occurring <20 km compared to <100 km. This approach led to a 75% reduction in false alerts over the study period.

5.3 Tier 3: Analyze Available Lightning Data for Eruption Nowcasting

Once a system has been set up to gather near-real time lightning data from an existing network, the next step is to move from eruption

detection to characterization: Identifying what the lightning data reveal about eruption source parameters, such as those described in Table 2 and Sect. 4.2. An example would be calculating lightning rates and 2-D locations from an incoming data stream and comparing with an internal database to estimate vent location, eruptive onset and duration, plume height, plume morphology and trajectory. Such quantitative analyses are still at an early stage of development and would be best used in tandem with other monitoring observations. Since long-range systems only detect abundant lightning from plumes above the -20°C freezing level (the altitude of which varies by site and season), these measurements provide lower fidelity information compared to local sensors (Tier 4).

5.4 Tier 4: Install Local Sensors to Increase Level of Observational Detail

There are a variety of instruments that can be installed on or near a volcano to improve detection capabilities. Examples of local instruments include Lightning Mapping Arrays, electric field mills, and electric field change sensors. Though installing a local instrument requires training and maintenance to operate successfully, a key benefit is the potential to significantly improve response times to explosive eruptions by detecting electrical activity earlier than is possible with longer range systems.

For example, Behnke and McNutt (2014) compared the performance of a locally deployed Lightning Mapping Array to two long-range lightning location systems using data collected during the 2009 eruption of Redoubt Volcano. They found that the LMA always detected lightning earlier than the other networks (by 2–18 min), and sometimes was the only sensor that detected lightning. They also showed that those ground-based LLS were biased towards detecting spatially larger lightning, therefore these systems were likely missing the early onset of small-scale lightning. The detection

efficiency of one of the networks used in this study has improved since the 2009 eruption of Redoubt (Holzworth et al. 2021), but there has not yet been an opportunity to do an updated comparison. We note that a similar improvement in detection efficiency could be achieved by using locally-deployed electric field change sensors similar to those used by Vossen et al. (2021, 2022), which are less complex to install and maintain than LMA sensors.

It is important to recognize that not all volcanic plumes become sufficiently electrified to produce lightning (Smith et al. 2021), and even LMAs have limits on detection efficiency depending on their distance from the lightning source (radiated power falls off as $1/r^2$). However, the quasi-static electric field produced by the net charge in the plume can be detected if a field mill or similar sensor is located within 10–20 km of the plume. This method offers the best potential for detecting lightning-poor eruptions, including low-altitude gas plumes.

6 Summary

The integration of lightning into volcano monitoring offers observations and insights that complement established monitoring techniques. Despite being a relatively new field, there is already a wealth of observations showing the utility of monitoring electrical activity. Observations of lightning and electrification can help determine explosive eruption onset, duration, vent location, and the height, morphology and trajectory of an electrified volcanic plume. We have offered suggestions for adding volcanic lightning observations to a monitoring framework. While there is still more to learn and explore about volcanic lightning, adoption of lightning methodologies into volcano monitoring will hasten the advance of the field.

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Muography of Volcanoes

László Oláh and Hiroyuki K. M. Tanaka

Abstract

High-resolution visualization of the internal density composition and its time evolution in volcanoes could help to improve the understanding of underlying volcanic processes and improve the assessment of volcanic hazards. Cosmic-ray muons are elementary particles naturally produced in the atmosphere and are being everywhere on the surface all time. The muons are highly penetrating particles and some of them penetrate through even kilometric-sized volcanic edifices. Muography is an imaging technique that visualizes the density structure in large-scale structures by tracking of the penetrated muons—similarly to how X-raying is utilized for imaging in the human body. The recent progress in development of muon detector technologies has allowed us to operate instrumentation in harsh and varying environments surrounding volcanoes and utilize muography for passive, remote and

non-destructive imaging of the internal density structure of volcanoes. In this chapter, we present the principles of muography, the state-of-the-art of instrumentation and imaging techniques, and we highlight recent applications.

1 Introduction

Muography is an imaging technique that resolves the mass density distribution in large-sized geological and human-made structures via measuring the yield of penetrating cosmic-ray muons after or below these structures. Fig. 1a shows a schematic drawing of a volcano muography (Okubo and Tanaka 2012). A muographic observation system (MOS) is applied for directionally sensitive tracking and counting of muons arriving near-horizontally through the volcanic edifice. The amount of material and its evolution in time can be quantified by this technique. The first muography has been performed in the 1950s: George (1955) measured the yield of cosmic-rays in a tunnel in an Australian mine to estimate the thickness of the overburden materials. In the 1960s, Alvarez et al. (1970) installed muon detectors inside the Khephren pyramid, Egypt for searching hidden chambers in the pyramid via comparing the measured and simulated

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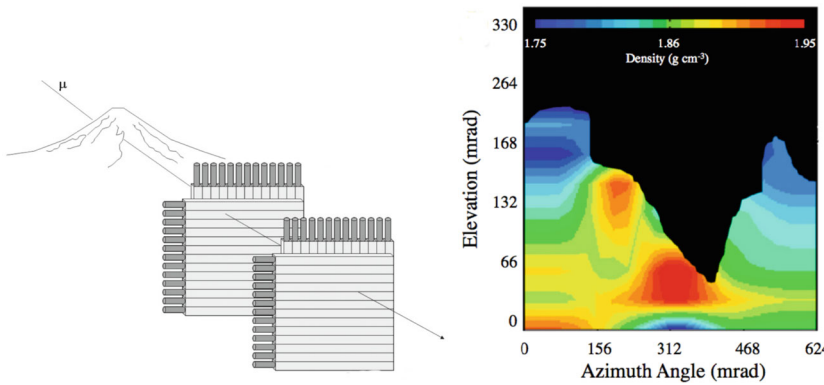


Fig. 1 **a** A schematic diagram of volcano muography (Okubo and Tanaka 2012). **b** The first muographic image of an active volcano was captured about Mount Asama,

Japan after the eruption 2004 (Tanaka et al. 2007; Tanaka 2022). The red patch highlights a region with increased density due to the deposition of magmatic materials

muon yields. Muon detectors were optimized from laboratory-sized indoor infrastructures to fieldable instruments during the next three decades. The first trial of volcano muography was conducted in the 1990s: Nagamine et al. (1995) measured the muographic “shadow” of Mount Tsukuba, Japan and developed methodology for volcano muography. Tanaka et al. (2007) developed nuclear emulsion films for muography and captured the first muographic image of an active volcano. They resolved the internal density structure of Asama volcano, Japan after the eruption 2004. The muographic image revealed a region with increased density in the crater that was caused by the magma deposit (see the red patch in Fig. 1b). This pioneering result and consecutive works (Tanaka 2019, 2022) demonstrated that the naturally occurring muons allow passive, non-destructive and remote probing of the interior of volcanic edifices. Muographic technology and methodology are rapidly evolving since the 2010s, opening up new opportunities for both academia and industry (Oláh et al. 2022; Lechmann et al. 2021; Bonenchi et al. 2020; Bonomi et al. 2020; Lesparre et al. 2010). In the following sections, we focus on muography of volcanoes. We aim to overview the physics of muography (Sect. 2), the observational instruments (Sect. 3), the imaging techniques (Sect. 4) and discuss some recent developments for hazard assessment (Sect. 5) without any claim to completeness.

2 Experimental Aspects of Muography

Muons are elementary particles produced naturally with a mass that is approximately 200 times greater than the electron’s mass. Muons are part of the so-called ‘natural background radiation’ that is everywhere on Earth’s surface all time. Muons are observed with a finite yield of approximately 100 muons per square metre per second. The source of muons are particle physics processes initiated by the collisions of primary cosmic-rays (protons and lighter nuclei originating mainly from astrophysical sources) with the atmospheric nuclei (e.g., N_2 , O_2 , etc.) at the altitudes between 20 and 30 km above sea level (Gaisser 1990). Figure 2 provides a simplified picture of how the air showers pin down in Earth’s atmosphere. There are three main components of secondary cosmic-rays: (i) the muons, (ii) the electromagnetic shower and (iii) hadron cascade. Muographic imaging is utilizing the first component of cosmic-rays.

The muons are created at altitudes from 10–15 km mostly by the decay processes of pions and Kaons. The relatively long lifetime of $2.2 \mu\text{s}$ would allow muons to travel approximately 660 m in the atmosphere, however muons velocity is close to the speed of light in vacuum and the relativistic kinematic allows them to reach Earth’s surface. The muons’ yield has energy and zenith-angle dependence, $f(E, \theta)$, on the surface due

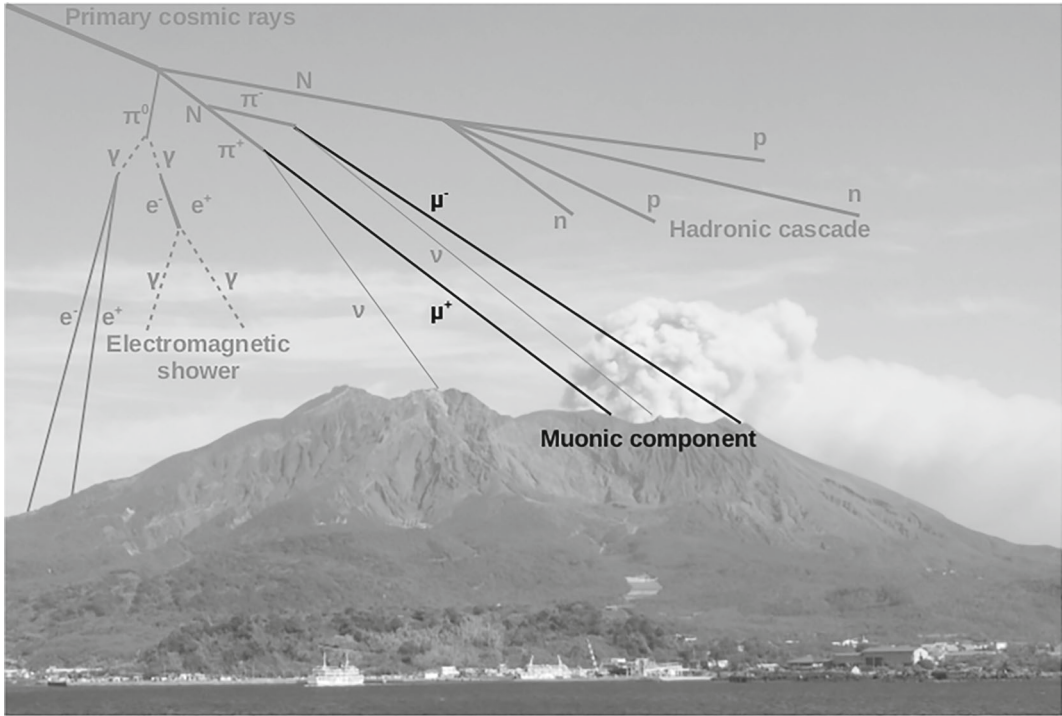


Fig. 2 A schematic drawing about the generation of electromagnetic shower, muonic component and hadronic cascade in the atmosphere is shown in a photograph of Sakurajima volcano (Credit: László Oláh)

to the different amount of air along the paths of muons at different zenith-angles that influence muons' decays and interactions (Cecchini and Spurio 2012). Geomagnetic effects, altitudinal and seasonal atmospheric effects influence rather the low-energy (<1 GeV) muons (Tanaka 2022), thus these effects have negligible influence on muographic imaging of kilometre-sized solid objects.

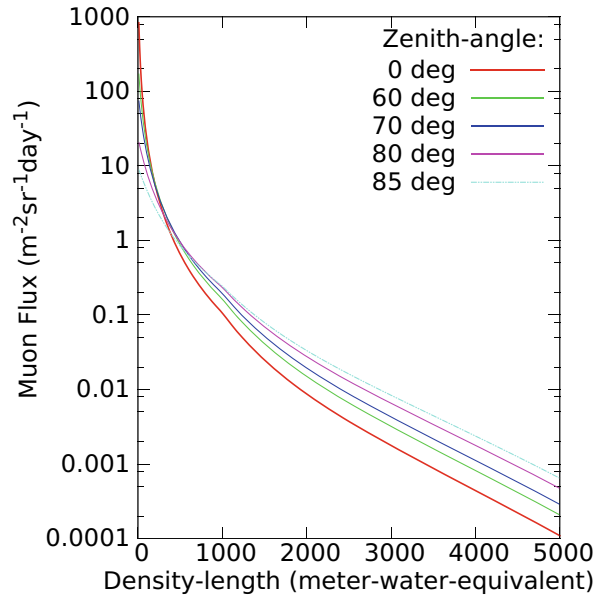
Muons suffer continuous and stochastic energy loss processes when they penetrate across a medium. The energy loss of muons depends mainly on the material thickness they traverse, i.e. integral of density (ρ) along the path-length (l). In this work, we label this quantity as the density-length (X). The energy loss can be described with the following formula:

$$-\frac{dE}{dX} = a(E) + b(E)E, \quad (1)$$

where $-dE/dX$ describes the energy loss per density-length unit, $a(E)$ and $b(E)E$ terms

describe the continuous and stochastic energy loss process, respectively. At smaller and medium energies, the continuous process dominates the total energy loss. At higher energies, the contribution from stochastic processes is increasing with the energy. There is a critical energy where the two kinds of energy losses equal and it depends on the penetrated medium. For example, the critical energies of muons incident into standard rock ($\rho = 2.65 \text{ g}\cdot\text{cm}^{-3}$), silicon dioxide and water is 693 GeV, 708 GeV, 1030 GeV, respectively. The relation between the energy of muons and their range, i.e. density-length of material that they are capable of penetrating, can be quantified by the Continuous Slowing Down Approximation (Groom et al. 2002). For example, muons lose approximately 0.2 GeV after every penetrated meter of water. The high-energy muons can penetrate even a few kilometres of materials. The expected flux of muons, $F(E_{min}, \theta)$, can be quantified by integrating the muon spectra from the E_{min} minimum energy required for muons to penetrate a given thickness of material, X :

Fig. 3 The attenuation of muon flux is shown as a function of the amount of penetrated materials



$$F(E_{min}(X), \theta) = \int_{E_{min}(X)} f(E, \theta) dE. \quad (2)$$

Figure 3 shows the attenuation of muon flux in water ($\rho = 1 \text{ g}\cdot\text{cm}^{-3}$) at different zenith-angles between 0° and 85° .

Besides energy loss, the muons suffer a lot of small scattering in the penetrated medium due to the electrostatic force acting between the muons and the nuclei of material. The multiple scattering results in an angular spread for muons and limits the resolution capabilities of muography, i.e., blurring the muographic images (Oláh et al. 2018). This effect is estimated to be 1 deg and 0.2 deg for 50 m and 1000 m standard rock, respectively (Oláh et al. 2019a). With the latter angular resolution, muography can resolve volcanic edifices with a spatial resolution of below 10 m from a few kilometres, which is appropriate for probing volcanoes (Oláh et al. 2018).

There are particles that are detected from the direction of the volcano, but these did not penetrate the volcanic edifice. These “fake muons” constitutes a background which can be grouped into scattered and hadronic backgrounds (Nishiyama et al. 2016). The scattered background consists of electrons, positrons and low-energy

muons which scattered in the atmosphere (Carbone et al. 2013; Oláh and Varga 2017). The hadronic background consists of protons, mesons as well as muons and electrons which created via hadronic interactions in the atmosphere or in the surrounding edifices located around the detector (Jourde et al. 2013; Ambrosino et al. 2015). These background particles increases the measured flux and decreases the muographically measured density-length. Identification and rejection of the tracks of these particles have to be considered for selection of measurement site (Niess et al. 2018; D’Alessandro et al. 2019; Vesga-Ramírez et al. 2020) and design of muographic observation system (Tanaka et al. 2014; Oláh et al. 2018; Mollica et al. 2022).

3 Design and Operation of Muographic Observation Instruments

Since muons have a finite yield on Earth’s surface and its value reduces to a 3–4 orders of magnitude smaller value after kilometre-thick volcanic edifices (Fig. 3), a careful experimental design has to be developed for the muography campaign. On

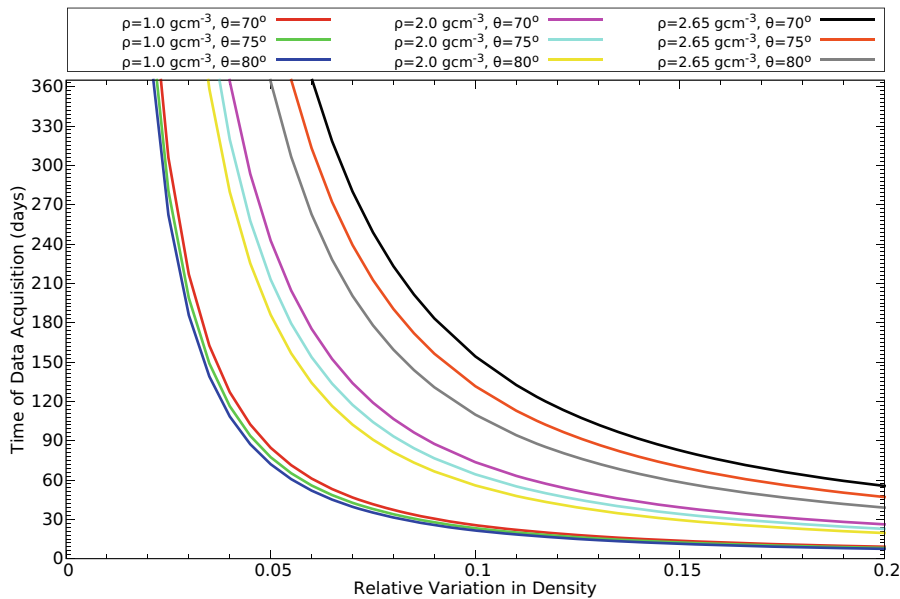


Fig. 4 Measurement time versus density resolution of muographic imaging

the one hand, the time required to resolve a given density variation should not exceed the period of volcanic phenomena that cause the variation in density. On the other hand, the detector acceptance (that incorporates the detector surface, covered solid angle and detection efficiency) has to be sufficiently large to achieve an angular resolution that is required to resolve the edifice and capture the volcanic processes.

To show an example, we modeled the muons' spectra and numerically integrated these for selected zenith-angles from minimum energies that were derived by simulations of muons through different density lengths of silicon dioxide. Figure 4 shows the estimated measurement times required to observe given relative density variations with 1 standard deviation using an observation acceptance of 10 cm²sr in the case of 1-km-thick craters with three different average densities at three different zenith-angles, respectively. For example, the measurement time of 60 days is required to observe a 10 % relative density length increase caused by ascending lava across a 1-km-thick crater with the average density of 2 g·cm⁻³ (see on the yellow curve). It is worth noting that the data acquisition time scales with the square of standard deviation.

Particle tracking detectors can be considered as cameras that capture and record the trajectories of charged particles that penetrate across their sensitive volume. Particle detector instrumentation applied for volcano muography have to be designed and optimized for the requirements of field operation (Marteau et al. 2022; Varga et al. 2022). Portable modules (detectors, electronics, support structures, power supplies, etc.) are applied to conduct muography even at hardly accessible sites, e.g. on the flanks of volcanic edifices. Another main requirement is the low-maintenance operation that is realized with modular observation systems to minimize the stopping of operation by failing of detector elements caused by either extreme weather events (typhoons, hurricanes, extreme humidity and temperature changes, etc.) or volcano activity (mainly ash falls and other volcanic ejecta). Minimization of power consumption is a crucial requirement for instruments that are operated by solar panels and batteries on sites where electricity network is not accessible for long-term operation. Detectors have to be designed to operate with stable and high detection efficiency to minimize the systematic effects and capture the density contrast occurring by volcanic phenom-

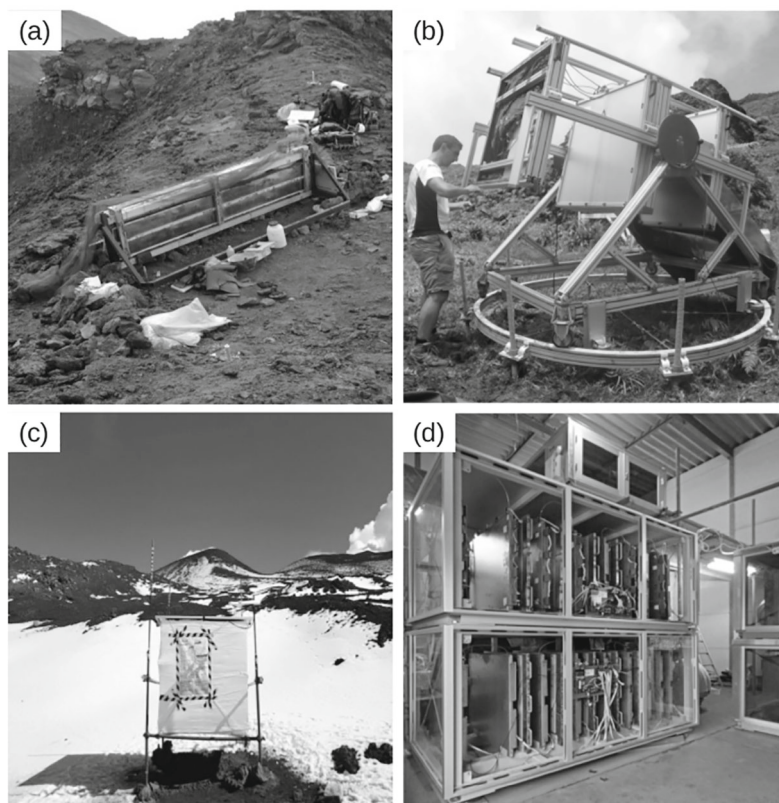


Fig. 5 Examples for Muographic Observation Systems (MOS) operated at active volcanoes. **a** Nuclear Emulsions have been applied for muography of Stromboli volcano, Italy (Tioukov et al. 2022). **b** and **c** Scintillator-based trackers are operating at the La Soufrière volcano, France

(Marteau et al. 2022) and at the North East Crater of Etna volcano, Italy (Lo Presti et al. 2020, 2022). **d** Multi-Wire-Proportional-Chamber-based MOS are applied in Sakurajima Muography Observatory, Japan (Oláh et al. 2021)

ena. Besides the detectors, volcano muography instruments are applying absorbers, scatter layers made from lead (Oláh et al. 2018; Macedonio et al. 2022) or iron or materials capable of creating Cherenkov radiation (Peña-Rodríguez et al. 2020) between the detectors to separate the background particles from muons that penetrated through the volcanic edifice. Figure 5 highlights four different modular muographic observation instruments operating (a) on the hardly accessible flank of Stromboli volcano (Tioukov et al. 2022), (b) at the La Soufrière volcano located on the Caribbean island (Gibert et al. 2022; Marteau et al. 2022), (c) on the snowy flank of the North-East Crater of Etna volcano (Lo Presti et al. 2018, 2022) and (d) at the frequently erupting Sakurajima volcano (Oláh and Tanaka 2022a,b; Varga et al. 2022).

Three different technologies have successfully been utilized in these muographic observation instruments. Each type has its pros and cons and the choice of technology depends on the purpose of the measurement campaign. The three main detector technologies are discussed in the following points:

1. **Nuclear emulsion detectors** are manufactured from a plastic base and emulsion gel with a total thickness of 200–300 μm and consist of AgBr micro-crystals and gelatin. Incident charged particles induce electronic processes in the detector. Chemical development of silver crystals visualizes the trajectories of charged particles. Emulsion films provide 3-dimensional particle tracking. Fig. 6a shows a microscope image of a nuclear emulsion

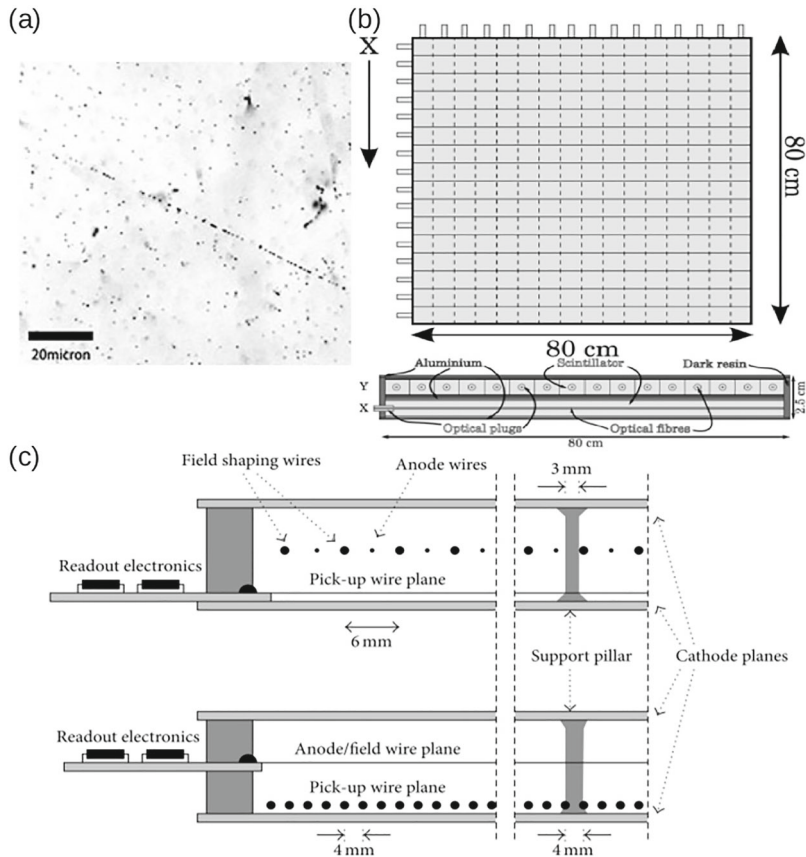


Fig. 6 Three detector technologies applied for muography. **a** A microscopic image of a nuclear emulsion that highlights a muon trajectory (Nishiyama et al. 2014). **b** Schematic drawing of a two-fold-segmented scintillator

detector is shown from upper and side view, respectively (Lesparre et al. 2012). **c** The cross-sections of a Multi-wire-proportional chamber are shown from two sides (Varga et al. 2016)

film with a remarkable cosmic muon track (Nishiyama et al. 2014). These detectors provide very good ($\sim \mu\text{m}$) position resolution. Nuclear emulsion detectors can operate without any electricity, maintenance and their structure is modular, thus one can perform measurements at sites which are difficult to access. This technology is very tolerant to mechanical shocks and water. However, it can not work above room temperature because the higher temperature increases the speed of fading effects in which the number of grains decreases along the tracks. Nuclear emulsions can continuously accumulate the tracks of charged particles from their production for about 6 months under the rate of cosmic rays at sea level. The tracks are reconstructed

by automated microscope scanning devices with a typical readout speed of a few tens of centimetres per hour. Although nuclear emulsion can not be applied for real-time muographic imaging, this technology has successfully been utilized for one-time surveying of the density structure in volcanic edifices (Miyamoto and Nagahara 2022; Miyamoto et al. 2022; Nishiyama 2022; Nishiyama et al. 2014; Tanaka et al. 2007; Tioukov et al. 2022).

2. **Scintillators** are the most widely used detectors in volcano muography (Marteau et al. 2022). Charged particles create photons in scintillator detectors with the typical yield of 1 photon per 100 eV of energy deposited by means of scintillation. Plastic scintillators are shielded from external light and internally

reflective for the created photons. These photons are detected most commonly with photomultiplier tubes (PMT). The scintillators produce relatively fast ($\sim$ nanoseconds) signals and the coincidence of multiple detector layers allows to detect charged particles with high efficiency. Such fast signals allow to measure the time-of-flights (TOF) of particles that helps to identify which particles penetrated across the tracking system from directions which opposite to the volcano's direction. The PMTs can work in a wide temperature range, which makes these technology applicable from areas with hot and humid climate to snow-covered mountains. Scintillator layers are segmented by strips with a typical width of 1–10 cm. To optimize their position resolution, one has to increase the number of PMTs which drastically increases the power consumption and cost of the detector system. Figure 6b shows an example of a two-fold-segmented scintillator detector (Lesparre et al. 2012). Scintillator-based tracking systems have successfully been utilized for real-time monitoring of active volcanoes, for example, see in Refs. (Tanaka 2022; Gibert et al 2022; Lo Presti et al. 2022). A new muography observatory, called MURAVES, is acquiring data at Mount Vesuvius, Italy with three scintillator-based tracking systems which cover a sensitive surface area of 3 m^2 (D'Errico et al. 2022; Macedonio et al. 2022).

3. In the **gaseous detectors**, the penetrating charged particles create typically 100 electrons per cm by means of ionization of gas (such as Ar or other noble gases) atoms. Electric fields formed around wires (Varga et al. 2022) or in micro-structures (Bouteille and Procureur 2022) or between resistive plates (Giammanco et al. 2022) induce electron avalanches that result in measurable signals (1000–10000 electrons). Front-end electronics are applied for amplification and digitization or discrimination of electric signals. Gaseous detectors provide a fair positional resolution of below a few mm and angular resolution of few mrad, a low material budget for a relatively

low price. The variation of environmental parameters affects the gas gain and, consequently, the tracking efficiency of gaseous detectors, thus correction on this effect is necessary to provide reliable tracking information during the data taking. The application of non-toxic and non-flammable gases allows environmental friendly operation (Nyitrai et al. 2021). Although a gas system is required for operation of these instruments, these can operate for a few months without maintenance due to the low gas consumption ($\sim 1\text{ l/h}$). The concept of gaseous detectors is robust, modular, and easily transportable, which makes it applicable in different environments. Muon tracking systems based on Micromegas (Bouteille and Procureur 2022), Multi-wire proportional chambers (MWPCs) (Varga et al. 2015; Varga et al. 2016; Varga et al. 2022; Varga et al. 2022; Gera et al. 2022) and Resistive Plate Chambers (RPCs) (Giammanco et al. 2022; Portal et al. 2013) have successfully been applied for muography. One example is the Sakurajima Muography Observatory (SMO) that is continuously observing the active craters of Sakurajima volcano, Japan with eleven MWPC-based tracking systems which cover a sensitive surface area of 8.25 m^2 (Oláh et al. 2021; Oláh and Tanaka 2022b; Varga et al. 2020, 2022).

4 Muographic Imaging Techniques

This section aims to briefly overview three different techniques that have been successfully applied for volcano muography.

4.1 Projective Imaging

A 2-dimensional projective density image is produced by a one-directional measurement (Fig. 1a) and it provides information about average density along quasi linear paths of muons. This imaging technique relies on the quantification of the flux of

penetrated muons or its ratio relative to the open sky flux measured from directions opposite to the volcanic edifice. The flux is determined by either Monte Carlo simulation or modeling of energy and zenith-angle dependent muon spectra using compiled experimental data. Using the information on the volcano topography, the path-lengths can be calculated and the average densities can be quantified for each paths. The Fig. 1b is an example of a 2D projective muographic image in which the density values are visualized as a function of azimuth and elevation angles. The Δq spatial resolution of these images can be approximated with the $\Delta\alpha$ angular resolution and L distance between the MOS and volcanic edifice: $\Delta q \approx \Delta\alpha \times L$. For example, a projective muographic image captured with an angular resolution of 10 mrad at a distance of 1 km from the volcano resolves the edifice with a spatial resolution of 10 m. The main limitation of this technique is that it can not provide a spatial resolution along the muon paths and there is uncertainty about the exact position and shape of the detected density anomaly.

4.2 Tomographic Imaging

Multi-directional imaging of volcanic edifices is overcoming the limitation of projective imaging and eliminating the superimposition of images of structures that are located outside of the volume of interest (Tanaka et al. 2010; Miyamoto and Nagahara 2022). The object to be imaged is divided spatially into n volumetric units, called voxels, with prior arranged average densities (ρ_j , where $j = 1, 2, \dots, n$). Tomographic imaging is performed by means of solving an inversion problem that describes the relation between the elements of the muographically measured density length vector ($\mathbf{X}$) and the voxel density vector ($\boldsymbol{\rho}$):

$$X_i = \sum_j^n L_{ij} \rho_j, \quad (3)$$

where L_{ij} is a matrix with the path-lengths that are determined from the topographic data of the volcano. The solution can be achieved by an iterative

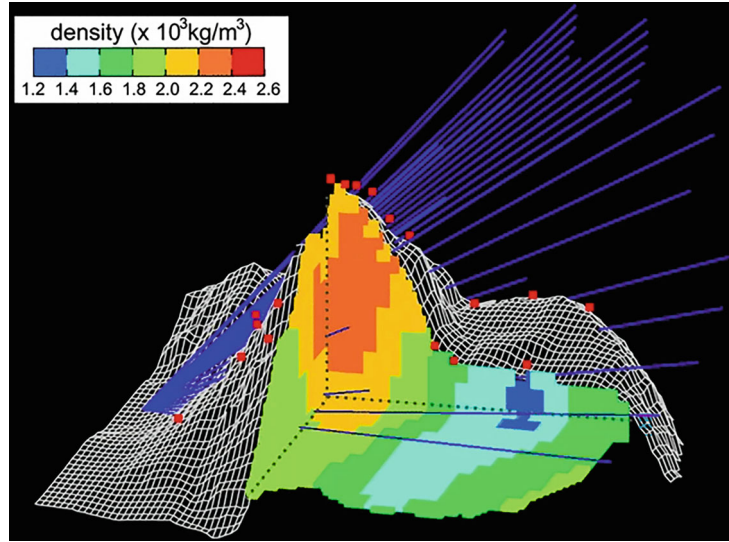
minimisation procedure that varies the ρ_i till X_i fit to the experimental data (Tarantola 2005). Different regulation methods are applied to avoid instabilities of inversion problems generated by e.g. data used from different directions. A recent study quantified how the accuracy of density measurements can be improved by increasing the directions. A muographic campaign is conducted around Orumuyama volcano for experimental demonstration (Miyamoto et al. 2022). Nagahara et al. (2022) reconstructed high-density zones in the scoria cone. Based on the muographic observations and topographic and geological constraints, they inferred that high-density zones are the central, highly welded vent of the scoria cone, three-directional radial dikes extending from the central vent.

The number of detected muons depends on the viewing solid angle covered by the muographic observation instrument, which is inversely proportional with the square of the distance between the muographic observation instrument and the volcano to be imaged. Consequently, land-based muography is limited by the observational distance, which is determined by the constraints on the local topography. Airborne muography has potentially overcome the topographic constraint and it can significantly reduce the measurement times from several days to a few hours in case of smaller volcanic edifices, such as the Unzen lava dome, Japan (Tanaka 2016). Such a development has the potential to allow the implementation of computational axial tomographic techniques for improving the quality of density images of volcanoes.

4.3 3D Density Imaging with Muography and Gravimetry

Measurement of gravity acceleration on the surface of volcanic edifices is a standard technique for surveying their near-surface density structure. A gravity measurement is sensitive to the distance R between the sensor and the object with average density ρ and volume V as follows: $\Delta g = G\rho V/R^2$, where G is the gravity constants. An

Fig. 7 3D density image of Showa-Shinzan lava dome obtained by joint analysis of muography and gravity data (Nishiyama et al. 2017). The 3D density image revealed cylindrical column of lava with a diameter of 300 m beneath the summit of the lava dome as it is shown by the orange colored volume. Red dots show the locations of gravity stations. Blue lines visualize the paths of muons from the sky to the detector



array of gravity sensors provides directional information on the detected density anomaly. The vertical component of the gravity anomaly at the i th gravity station is given by the following equation (Nishiyama et al. 2014):

$$\Delta g_i = \sum_j^n G_{ij} \rho_i, \quad (4)$$

where G_{ij} is the gravity contribution of the j th voxel to the i th gravity station for unit density. Integrated processing of gravity and muography data can improve the spatial resolutions of density imaging and allows to produce 3-dimensional density images of volcanic edifices:

$$\begin{pmatrix} \mathbf{X} \\ \Delta \mathbf{g} \end{pmatrix} = \begin{pmatrix} \mathbf{L} \\ \mathbf{G} \end{pmatrix} \rho.$$

This is a linear inverse problem. Nishiyama (2022) provides a comprehensive description of how to utilize linear joint inversion with muography and gravimetry data and overviews the different approaches that are applied for handling of small density fluctuations by means of kernel analysis (Jourde et al. 2015) and background noise by introducing density offsets (Rosas-Carbajal et al. 2017; Lelièvre et al. 2017; Barnoud et al. 2021).

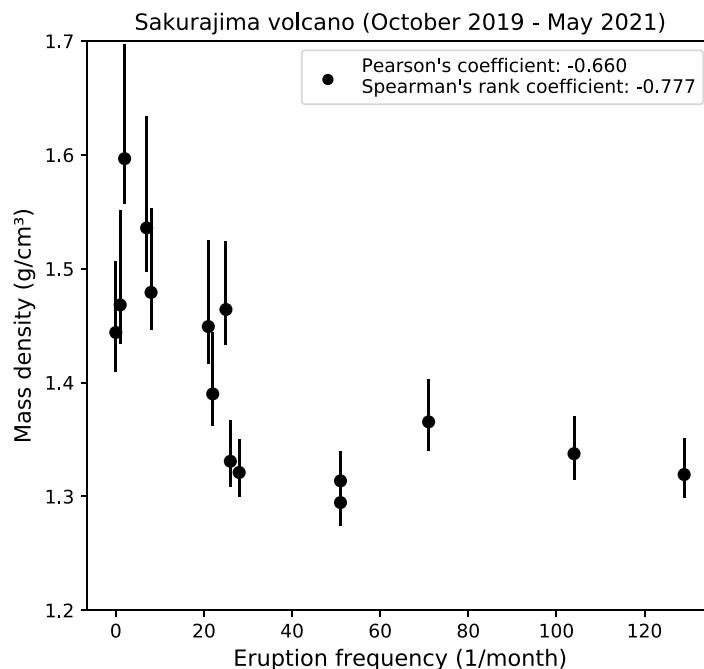
Joint inversion of muography and gravity data has successfully been applied to reconstruct a

cylindrical column of lava with a diameter of 300 m beneath the summit of Showa-Shinzan lava dome (Nishiyama et al. 2017) (Fig. 7), to reveal an extensive, low-density anomaly where the most active part of the volcanic hydrothermal system is located underneath the southern part of La Soufrière volcano (Rosas-Carbajal et al. 2017), to delineate a trachytic core of the dome from its surrounding talus in the Puy De Dôme volcano (Barnoud et al. 2021). Recently, a machine learning approach was also tested for 3-dimensional density imaging of Showa-Shinzan lava dome (Cosburn et al. 2022).

5 Assessment of Volcanic Hazards with Muography

Volcanoes pose direct (e.g., eruptions, pyroclastic flows, tephra fall, etc.) and indirect (such as lahars or tephra deposition) hazards to the surrounding landscape, economy and population within a distance of a few hundreds of kilometres. Continuous monitoring of mass changes related to material deposits and movements either inside or on the surface of volcanic edifices can contribute to the assessment of volcanic hazards and mitigate the possible catastrophic impacts. The potential of muography for hazard assessment of two types of hazards is presented

Fig. 8 Muographically measured mass density is shown as a function of monthly eruption frequency at Sakurajima volcano



via the case studies described in the following subsections.

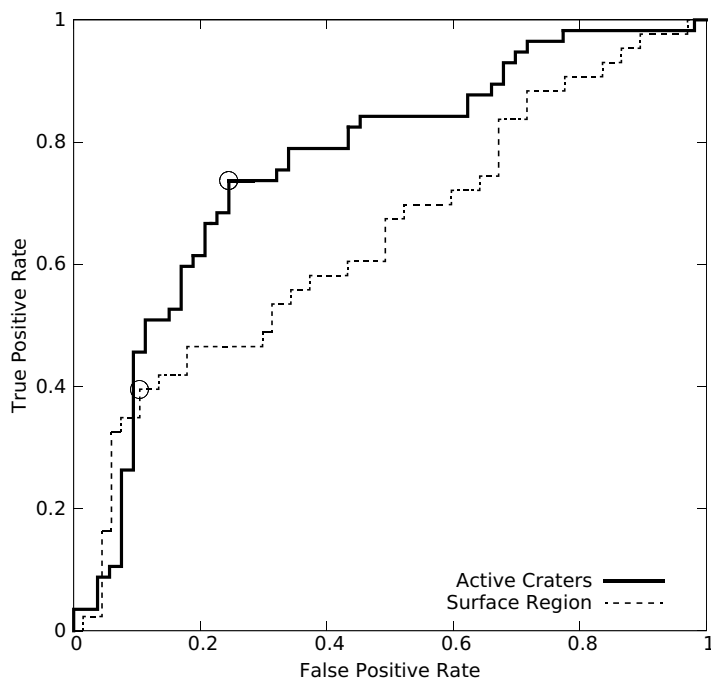
5.1 Muography of the Subsurface Evolution and Movement of Magma

Hazard assessment relies on monitoring data originated from different phenomena (e.g. ground deformation, seismicity, gas emission, etc.) that induced by magma evolution and movement. However, these phenomena not necessarily followed by eruptions. For example, a global study showed that 46 % of deformed volcanoes erupted (Biggs et al. 2014). Monitoring the subsurface mass density changes is expected to reveal the casual physical mechanism and improve the evaluation of monitoring signals acquired for hazard assessment. Time-sequential muography was applied to capture mass density changes related to the movement of magmatic materials (Tanaka et al. 2014; Oláh et al. 2019b) and hydrothermal activities (Jourde et al. 2016) inside different volcanic edifices.

In a recent work, we conducted simultaneously the time-sequential muography of the volcanic conduit and ground deformation monitoring of the craters of the southern peak of Sakurajima volcano, Kyushu, Japan throughout its eruptive and dormant periods (Oláh et al. 2023). The mass density increased beneath the crater during the inflation of volcanic edifice, when the eruption frequency was low. The mass density decreased during the deflation of volcanic edifice, when the eruption frequency was high. Figure 8 shows mass density with 1 standard deviation errors as a function of monthly eruption frequency. These data show a moderated inverse correlation with a Pearson's coefficient of -0.660 (Spearman's rank coefficient of -0.777) between density and eruption frequency.

The periods of low eruption frequency are associated with the plug formation in the conduit, which traps pressurized magmatic gas, leading to inflation. The periods of high eruption frequency are associated with the absence of the plug, which allows gas to escape, leading to deflation. These observations demonstrated that muography can reveal in-conduit physical mechanism and explain

Fig. 9 Receiver operating characteristic are shown for the active crater and a surface region of Sakurajima volcano with solid and dashed lines, respectively



the link between ground deformation and eruption frequency.

5.2 Short-Term Eruption Forecasting

Machine learning of the time series of muographic images can be used for assessing the occurrence of short-term eruptive events. The applicability of this approach has been tested to the active craters of Sakurajima volcano (Nomura et al. 2020; Oláh and Tanaka 2022a). Machine learning techniques have potential to extract the hidden features in the consecutive muographic images of volcano that are related to internal mass changes, and predict the occurrence of future eruptions via binary classification.

In our pilot study Oláh and Tanaka (2022a), a convolutional neural network (CNN) was utilized for machine learning of seven consecutive daily projective images captured by MWPC-based tracking systems of Sakurajima Muography Observatory from November 2018 to June 2020 for predicting the explosive eruptions of the Central Craters. The muographic images were captured independently for the region of the

active craters and for the surface region where volcanism does not occur. Each image had an angular resolution of 23 mrad that corresponded to a spatial resolution of 60 m from a distance of 2,800 m. The pixels in these images represent the muon flux values measured throughout these volcano regions. The set of images was divided into three subsets for training, validating and testing of CNN. Receiver Operating Characteristic (ROC) analysis (Fawcett 2006) was performed for evaluating the performance of CNN. Figure 9 shows ROC curves determined for the active craters (solid line) and the surface region (dashed line). The true positive rate represents the sensitivity, i.e. predicted eruptions per number of all eruption, and the false positive rate represents a ratio of fake predictions.

As it was expected, the Area Under the Curve (AUC) for prediction of eruptions occurring in the active Central craters was found higher (0.76) than AUC for the surface region (0.64) of the volcano due to the larger mass changes inside the volcanic edifice caused by movements of magmatic materials. The comparison of the results for the Showa crater (Nomura et al. 2020) and the Central craters (Oláh and Tanaka 2022a) revealed that the

Fig. 10 A photograph of the southern peak of Sakurajima volcano from the site of Sakurajima Muography Observatory. Black lines highlight the monitored surface region of volcanic edifice



improved muographic imaging resolution does not necessarily result in higher performance for the CNN because it also depends on the eruptive activity (i.e., the amount of training data), amount of mass changes beneath the craters and the geometry of the crater. The social implementation of eruption forecasting is expected to be realized by means of interpretable machine learning of combined data sets consisting of conventional (e.g., seismic, gas, etc.) and muographic monitoring data.

5.3 Assessment of Indirect Volcanic Hazards

The volcanic ejecta deposition can disturb the drainage basins on volcanoes and pose hazards within a few tens of kilometres radii around the craters even during dormant periods. Monitoring of the amount of sedimented volcanic ejecta would allow observing the erosion processes before the destabilization of the volcanic edifice and the occurrence of post-eruptive lahars and it would help to estimate the amount of remobilised materials by lahars, thus contribute to the mitigation of lahars. Conventional remote sensing techniques have limitations for observation of topographic changes due to the constraints on observational time and cost. Muographic monitoring can be a useful complementary technique for measuring the long-term changes in the amount of ejecta deposits (Tanaka 2020) and short-term erosion processes (Oláh et al. 2021).

Muography was conducted to monitor the mass changes through the surface region of the southern peak of Sakurajima volcano, (see the selected area within the black lines in Fig. 10). Figure 11 shows

the 40 days moving average of relative mass variation (black dashed line) with 1 standard deviation bands (gray bands) from 21st April 2019 to 1st December 2020. This quantity was calculated relatively to the total mass measured throughout the selected region between 12th March and 21st April in 2019. The relative mass significantly increased from September 2019 in accordance with the increase of eruptive activity (Fig 11a) due to the deposition of volcanic ejecta. This observation was found consistent with the masses of total volcanic ejecta, which were measured to approximately 0.25 Mt and approximately 2 Mt for periods from September 2019 to July 2020 and from April to September 2019, respectively (Japan Meteorological Agency, Report of Coordinating Committee for Prediction of Volcanic Eruption No. 145. 2019; Japan Meteorological Agency, Report of Coordinating Committee for Prediction of Volcanic Eruption No. 146. 2020). It is worth noting that the muographic observation confirmed that the amount of volcanic ejecta is increasing with the time that lasts between two eruptions, as shown by the mass increase after the eruption occurred in August 2021.

Besides the long-term mass increase, short-term mass decreases were also observed. These mass changes were caused by hydrogeomorphic changes induced by lahar events (Fig. 11b). These lahars were triggered by intensive rainfall as shown by the maximum precipitation per hour in Fig. 11c. Further mass decrease is assumed by the erosion of the tephra deposition. These processes were induced by rainfall that were observed continuously during the typhoon season from August to October 2020. We have to note that the muographic observation of mass decreases due

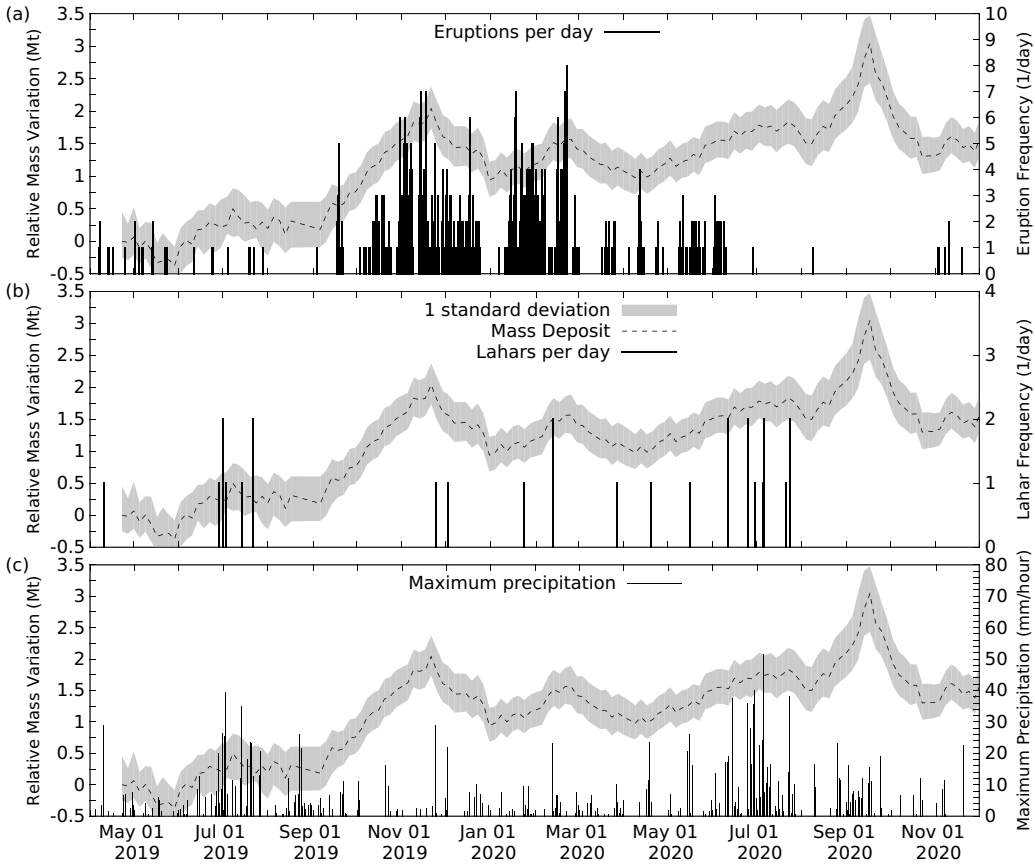


Fig. 11 The relative variation of total mass measured through the selected volcano regions is shown relative to the total mass measured from 12th March to 21st April, 2019. The 1 standard deviation error band of relative mass

variation (gray brand) is shown with **a** the eruption frequency, **b** the frequency of lahars and **c** the maximum precipitation of rain fall (black impulses) as a function of time

to hydrogeomorphic changes is limited when the tephra deposition extinguishes or overwhelms these processes. In conclusion, muography has the potential to reveal the topographical changes that can induce post-eruptive lahars. Decreasing the time-sequences of muographic measurements has the potential to contribute to the modeling of the erosion of the volcanic edifice and assessment of volcano hazard levels.

6 Summary

Muography is a passive and non-destructive imaging technique that allows remote near real-time monitoring of volcanic edifices and other large-

sized structures via tracking the naturally occurring cosmic-ray muons. Muography employs different kinds of technologies (e.g., scintillators, gaseous detectors and nuclear emulsions) that has to be chosen accordingly to the target and the field conditions. Muography can be applied as a standalone monitoring technique or it can be combined with other density sensitive methods to reconstruct 3-dimensional density distribution in volcanic edifices. The applicability of muography has already been demonstrated for monitoring the changes in the mass density of subsurface volcanic materials and their movements. Muography observatories are being under development at the Sakurajima volcano, Mount Etna, Mount Vesuvius, La Soufrière volcano and other volcanoes.

Here, we highlighted the latest results from the Sakurajima Muography Observatory: we demonstrated that muographic monitoring of mass density through volcanic conduit helps to explain the casual physical mechanism behind the changes in other monitoring signals, machine learning of muographic images is a promising approach to contribute to short-term eruption forecasting, and muographic monitoring the mass changes on the volcano's surface provides useful information for modelling the pyroclastic deposition and erosion. Efficient amalgamating of high-energy physics and Earth sciences is expected to make cosmic-ray muography a useful complementary technique for volcano monitoring and contribute to the assessment of related hazards.

Acknowledgements The authors acknowledge the support of Ministry of Education, Culture, Sports, Science and Technology, Japan (MEXT) Integrated Program for the Next Generation Volcano Research. LO is supported by the HUN-REN Welcome Home and Foreign Researcher Recruitment Programme KSZF-144/2023. and the Hungarian NRDI Fund research grant TKP2021-NKTA-10. The technical support provided by the REGARD group of HUN-REN Wigner RCP is gratefully acknowledged.

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Fiber Optic Sensing for Volcano Monitoring and Imaging Volcanic Processes

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Abstract

This chapter describes fiber optic sensing methodologies and their applications for understanding volcanic structure and processes. We assess their benefits for volcano

monitoring and offer possible solutions to address their challenges. The physical principles at the basis of fiber optic sensing technologies have been known for several decades. These principles are related to various processes involving electro-magnetic interactions of light sent by a laser within glass. Intrinsic physical properties of glass within the optical fiber, when engineered appropriately and interrogated with an adequate light source, enable us to access a number of environmental parameters, such as temperature, strain and rotation over a large frequency range. However, only recently developed instruments have been able to sense these parameters efficiently, either at a point or densely in a distributed way for geophysical and volcanological applications. Rotational sensors allow us to measure the rotational components of the seismic wave field, which have been discarded in the past. Distributed fiber optic sensing provides access to quasi-continuous measurements of temperature, strain and strain rate along km-long fibers with a high spatial resolution (meter) and sampling rate (kHz). We show examples on volcanoes both on land and in submarine environments. We demonstrate that data from optical strainmeters, rotational sensors, distributed fiber optic strain and/or temperature sensing can reveal

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unknown structural features and processes in volcanoes. These examples testify that fiber optic sensing methodologies owe to be implemented as additional tools for improved volcano monitoring and for volcanic crisis management.

1 Introduction

Approaches and techniques for monitoring active volcanoes have significantly evolved in recent years, mainly due to innovations in instrumentation, to denser spatial observations and to an improved interpretation of data through better integration of geophysical and geochemical observations (Surono et al. 2012). The aim of volcanology is to forecast the behavior of a given volcano and issue timely alerts for effective hazard assessment and risk management (Witze 2015). To achieve this goal, models of mass and energy transfer are necessary. These models require the knowledge of accurate details of the distribution of physical properties within the volcano, of the full seismic wave field and of key thermodynamic properties and transfer processes within the volcanic system. To achieve such acute description, volcanologists deploy instruments to measure physical and chemical parameters on volcanoes and interpret their spatial distribution and temporal variations in relation with volcanological and geological observations. For example, the use of large-N seismometer networks to densely observe ground motions has enabled volcanologists to gain additional knowledge on volcano seismic structure and processes (Hansen et al. 2016; Yeh et al. 2021). The analysis of the parameter variations over time recorded with multiple instruments, contributes to evaluating the status of the volcanic activity and supports volcano monitoring.

This chapter aims to illustrate how the use of fiber optic sensing methodologies can provide valuable information for achieving various goals in volcanology. This includes understanding structural features and volcanic processes, which can contribute to improved volcano monitoring.

Fiber optic sensors offer several advantages over conventional sensors (Lu et al. 2019; Blanc et al. 2022). On the one hand, sensing can be performed remotely via optical fiber due to the low transmission losses of light within the optical fiber. On the other hand, optical fibers are highly sensitive to external physical processes, allowing for accurate recording of new observables (such as translation, rotation and strain) at a specific position, or at series of distributed locations along a fiber (which can span tens of kilometers), with a dense spatial resolution (e.g., meter, using Distributed Fiber Optic Sensing for temperature and strain). Furthermore, optical fibers are suitable for use in harsh environments due to their immunity to external electromagnetic interference, high temperatures resistance, and ability to withstand corrosive conditions. Additionally, fiber optic cables are lightweight, compact, flexible, easy to deploy, and cost-effective, requiring low maintenance. All these merits explain why fiber optic sensing has been used for many years in a wide range of applications, including civil engineering, mining and energy exploration, and environmental sciences, especially in harsh and challenging-to-access environments (Miah and Potter 2017). The technologies associated with fiber optic sensing have shown their potential in replacing conventional electromechanical-based temperature and vibration sensors. This justifies the potential of expansion of their use also in volcanology.

The principles behind fiber optic sensing were discovered several decades ago by Rayleigh (1881), Sagnac (1913a, b), Brillouin (1914), and Raman (1928). The measurement involves sending light through an optical fiber and analyzing changes in light properties, such as amplitude and/or frequency, after it interacts with the medium it travels through, such as glass fiber. When the environment in which the fiber is located undergoes changes in physical parameters, such as temperature, strain or rotation, the properties of light are modified due to the altered interactions between the light and the glass. The Sect. 2 will provide a detailed explanation of these principles and processes.

However, the implementation of these principles in practice has only been happening in the last few decades for an increasing number of applications, at a reasonable cost. These advances can be attributed to simultaneous substantial technological innovations, particularly in optoelectronics and photonics, which now enable photonic scientists to manipulate light and measure tiny phase shifts at a very high sampling rate. Advancements in fiber optic cable design and manufacturing, as well as improvements in laser (as the source of light) accuracy and stability, have contributed increased accuracy and resolution of fiber optic technologies. Additionally, in computer science, digital information can be processed more quickly using smaller and more efficient electronic chips and new processing algorithms. These advancements enable the recording of new geoscientific information with high temporal and spatial resolutions and improved accuracy. Consequently, optical fiber technologies have become increasingly popular in recent years for geophysics and geoscientific applications (Wassermann et al. 2016; Matias et al. 2017; Bastianini et al. 2019; Lu et al. 2019; Zhan 2019; Lindsey and Martin 2021; Chang et al. 2022; Moreno et al. 2022; Noe et al. 2023). Below, we summarize the three main approaches to fiber optic sensing: light transmission sensing, point sensing and distributed sensing.

Light transmission sensing involves analyzing changes in light transmission delay or polarization, occurring within an optical fiber between the point of emission and reception. These changes are linked to perturbations of the refractive index of the fiber glass caused by external vibrations or disturbances, such as seismic waves. This method has been used with trans-oceanic telecom fiber optic cables to detect and/or locate earthquakes over large distances (1000s km), using disturbances in transmission delays (Marra et al. 2018; Bogris et al. 2022) and polarization (Palmieri and Schenato 2013; Zhan et al. 2021). By using this technique on several successive shorter cable segments, earthquakes on the mid-oceanic ridge can be located (Marra et al. 2022). This opens the possibility

of monitoring inaccessible submarine volcanoes using existing and future telecom networks. Transmission delay or polarization methods may be used in volcanology *sensu stricto* in the near future.

Fiber optic point sensing involves the analysis of changes in light properties in dedicated small size sensor (0.01–0.1 m scale) in order to measure locally an evolving physical parameter affecting the light properties. Several such instruments have been developed to measure seismic ground motion (Feron et al. 2020), rotation (Bernauer et al. 2012, 2018, 2021; Wassermann et al. 2020; Brokešová et al. 2021), tilt (Chawah et al. 2015) and strain (Ferraro and De Natale 2002; He et al. 2013; Coutant et al. 2015). Fiber optic rotational sensors have been proven successful in controlled huddle tests, in which many similar sensors record at the same time and same location (Izgi et al. 2021). The sensors were deployed for various purposes, including the analysis of tectonic earthquakes in Italy (Simonelli et al. 2018; Yuan et al. 2020), micro-zonation of damages after significant earthquakes (Wassermann et al. 2016; Keil et al. 2021, 2022), exploration seismology (Schmelzbach et al. 2018), and tracking moving sources (Yuan et al. 2021). Rotational sensors can also help to correct for tilt contamination of records from nearby conventional seismometers (Bernauer et al. 2020), to correct measurements on the seafloor (Lindner et al. 2016), or to directly study microseisms generated in the ocean (Hadziioannou et al. 2012; Tanimoto et al. 2015). Rotational sensors have been shown to measure meaningful volcano-seismic signals on volcanoes, such as in Hawaii, USA (Wassermann et al. 2020), on Stromboli, Italy (Wassermann et al. 2022) and at Etna, Italy (Eibl et al. 2022).

Distributed Fiber Optic Sensing (DFOS) involves analyzing changes in light properties after it has interacted with the structure of the fiber glass itself. DFOS typically uses an interrogator device connected to a single optical fiber within a fiber optic cable, which can be deployed on purpose or in existing infrastructure. The interrogator contains a laser that

sends light through the fiber. The light interacts with the glass structure of the fiber, typically variations of the glass refractive index, via e.g., scattering processes (see Sect. 2 for full details). Part of the scattered light travels back to the interrogator where it is analyzed by a photodetector also inside the interrogator. The properties of the light change in relation to changes in environmental parameters, such as temperature and strain, acting on the fiber glass structure. Thus, the fiber serves not only as a means of transmitting light, but also as a sensor. DFOS is capable of probing kilometers of fiber at once due to the low attenuation during light propagation. As scattering processes occur continuously along the fiber, measurements can be obtained at any chosen spatial interval, making DFOS a distributed sensing method. DFOS enables distributed sensing over distances of 10s-kilometer, with data typically measured every couple of meters. This makes it attractive for a wide range of applications.

DFOS has been developed to measure temperature (Hartog 1983; Li et al. 2015), dynamic strain (Parker et al. 2014) and static strain (Horiguchi et al. 1989). Local external perturbations along the sensing fiber, such as temperature and strain, can be measured by analyzing the amplitude, the frequency, the polarization or the phase of the light (Lu et al. 2019). DFOS has been widely used in various applications due to its ability to probe the entire length of the fiber for temperature and strain at high spatial resolution. For instance, it has been used to investigate line cuts and quality in telecommunication networks (Barnoski and Jensen 1976, Barnoski et al. 1977; Philen et al. 1982) and in ensuring perimeter security (Taylor and Lee 1993; Szustakowski and Zyczkowski 2005). DFOS has also been used in petroleum and geothermal industrial applications to log borehole structure with Vertical Seismic Profiling (Daley et al. 2013; Madsen et al. 2013, 2016; Frignet and Hartog 2014; Hartog et al. 2014; Zwartjes and Mateeva 2015; Willis et al. 2016; Correa et al. 2017; Martuganova et al. 2022; Schölderle et al. 2022), to profile well temperature (Reinsch et al. 2013). DFOS has also been used for monitoring

well integrity (Lipus et al. 2018), fluid flow during hydraulic fracturing (Molenaar and Cox 2013; Richter et al. 2019), and reservoir microseismicity (Verdon et al. 2020). DFOS has been applied in various other applications including structural health monitoring (Trebugov et al. 2016; Barrias et al. 2017) and land subsidence monitoring (Wu et al. 2015).

Applications in non-industrial Earth Sciences are more recent. They often face challenges due to harsh environmental conditions. DFOS has been used to accurately and precisely characterize the Earth's crust over distances ranging from 0.1 to 100 km. These applications cover a range of topics including ice monitoring in a lake (Castongia et al. 2017) and in glaciers (Walter et al. 2020; Klaasen et al. 2021), landslide monitoring (Kogure and Okuda 2018), teleseismic earthquake detection (Lindsey et al. 2017; Jousset et al. 2018; Yu et al. 2019) and local earthquake detection and location (Jousset et al. 2018; Klaasen et al. 2021; Nishimura et al. 2021). Krawczyk et al. (2019) conducted research on monitoring urban areas. Jousset et al. (2018) and Krawczyk (2021) conducted research on crustal structure and monitoring on-shore, while Lindsey et al. (2019), Jousset (2019), Sladen et al. (2019), Williams et al. (2019) and Janneh et al. (2023) focused on submarine off-shore topics, such as microseism or submarine life (Landrø et al. 2022). Global seismology also benefits from the large number of available infrastructures (Jousset et al. 2023; Wuestefeld et al. 2023). The success in using already deployed standard telecom fibers (Jousset et al. 2016; Lindsey et al. 2017; Sladen et al. 2019; Williams et al. 2019) makes DFOS particularly attractive for volcanoes in urban areas and submarine environments, such as Campi Flegrei and Vulcano (Currenti et al. 2023), in Italy. However, most volcanoes lack telecom networks, requiring the deployment of optical cables for fit-to-purpose experiments and potential monitoring (Contrafatto et al. 2019; Jousset et al. 2019; Currenti et al. 2021; Klaasen et al. 2021; Fichtner et al. 2022; Jousset et al. 2022).

This chapter focuses on technologies and applications that address two quantities relevant

in volcanology: temperature and the full seismic wave field (translation, strain and rotation). These quantities are most appropriate for yielding ground property distributions and structural features at volcanoes and for characterizing processes to improve volcano monitoring and hazard assessment. The chapter is structured as follows: Sect. 2 describes the various optical techniques, highlighting the ability of fiber optic sensing in measuring accurately the full seismic wave field, including translational displacements, rotational and strain components, across a wide frequency range. Section 3 presents the current status and advancements in Point Fiber Optic Sensing and in Distributed Fiber Optic Sensing for volcanology, with examples from Canada, France, Germany, Iceland, Italy and Japan. These examples demonstrate the ability of fiber optic technologies to achieve the following: 1. improve the inference of seismic wave field properties; 2. provide a detailed characterization of subsurface volcanic layers and image faults; 3. detect and locate volcanic earthquakes; 4. quantify volcano deformation and describe its relationship to the tectonic environment; 5. detect small signals related to fluid movement, such as monitoring bubbles in a volcanic lake, and quantify and locate volcanic explosions. In Sect. 4, we address the limitations and challenges of fiber technologies, and propose potential solutions for real-time operational volcano monitoring. Section 5 concludes by examining the future of fiber optic technologies for research, volcano monitoring, and volcanic crisis management.

2 Fiber Optic Principles and Methods for Seismic Wave Field and Temperature Measurements

Volcanic phenomena can cause deformation, such as the rotation, tilt and translation of blocks of rocks at different spatial and temporal scales. Therefore, volcanology requires a description

and observation of the complete seismic wave field across a wide frequency range (from months to hundreds of Hz). However, until recently (Matoza and Roman 2022), volcano-seismology was unable to measure the full seismic wave field, in particular its rotational and strain components (Thelen et al. 2022), due to the lack of adequate instruments. This has changed with the development of new fiber-based instrumentation that can measure rotation or strain with small amplitude resolution (nanoradians to microradians or nanostrain to microstrain, respectively) over a broad frequency range (0.0001–100 Hz).

This section provides a brief overview of linear seismology before discussing the physical principles behind fiber optic technologies that describe the ground motion (translation, strain and rotation) and temperature (see also Table 1). To ensure a comprehensive description, we refer to several reviews due to the wide range of tested and existing technologies. In addition to Hartog's (2017) general introduction, the literature comprises general reviews by Kersey (1996), Grattan and Sun (2000), Lu et al. (2019), Pevec and Donlagic (2019), Fenta et al. (2021) and Moreno et al. (2022). Other literature focus on more specific aspects of fiber optic technologies such as Fabry-Perrot technologies (Nur et al. 2016), distributed temperature sensing (Ukil et al. 2011), Brillouin scattering (Bao et al. 2021), and distributed dynamic strain sensing, also known as distributed acoustic sensing (Masoudi and Newson 2016; Reinsch et al. 2021; Gorschkov et al. 2022; Liu et al. 2022; Masoudi and Brambilla 2022; Sun et al. 2022). Ramakrishnan et al. (2016) reviewed applications for composite materials. Miah and Potter (2017) studied strain and temperature for geophysical applications, while Schenato (2017) focused on geo-hydrological applications. Di et al. (2018) explored deformation applications, Hartog et al. (2018a, b) monitored marine infrastructures, Zhu et al. (2022) monitored linear infrastructures, and Butt et al. (2022) conducted research on environmental monitoring.

Table 1 Summary of the main fiber optic techniques and their applications in volcanology

	Acronym	Method	Volcano	Time and space samplings	Volcano applications	Bibliography
Rayleigh	OTDR	Incoherent distributed Rayleigh power sensing				Rayleigh (1881) Barnoski et al. (1977)
	OFDR	Swept wavelength interferometry				Kreger et al. (2016)
	ϕ -OTDR (DAS DVS)	Coherent distributed Rayleigh power sensing	Reykjanes Etna Aso Meagler Grímsvötn Laacher See Stromboli	Seismic, high frequency applications Challenge for low frequencies, except in engineered fiber Typical freq: 0.1–500 Hz Typical sensitivity: few nanostrain Gauge length 5–30 m (for seismic usually 10 m)	Jousset et al. (2018) Currenti et al. (2021) Nishimura et al. (2021) Klaassen et al. (2021) Jousset et al. (2022) Fichtner et al. (2022) Currenti et al. (2023) Diaz-Meza et al. (2023) Biagioli et al. (2024) This chapter	Parker et al. (2014) Hartog (2017) Posey et al. (2000) Peng et al. (2014) Tu et al. (2015) He et al. (2018) Chen et al. (2019)
	WS-OTDR					Liehr et al. (2018) Liehr et al. (2019)
	CP- ϕ -OTDR	Rayleigh and Raman scattering		1 mK/4 nanostrain		Pastor-Graells et al. (2016) Xiong et al. (2018)

(continued)

Table 1 (continued)

		Acronym	Method	Volcano	Time and space samplings	Volcano applications	Bibliography
Brillouin	Deformation/temperature	BOTDR	Brillouin OTDR	Etna	Long term deformation. Low sensitivity at high frequency Typical frequencies: minutes Typical sensitivity: microstrain Gauge length 1–3 m	Gutscher et al. (2019) Murphy et al. (2022) Gutscher et al. (2023)	Brillouin (1914)
		BOTDA					Horiguchi et al. (1989)
		BOCDA	Correlation-base technique				Hasegawa and Hotate (1999)
		BOFDA					Nöther et al. (2008) Wosniok et al. (2009) Bernini et al. (2012)
Raman	Temperature	ROTDR/ROFDR	Raman OTDR/OFDR	Erebus Campi Fleigrei	10 min	Curtis and Kyle (2011) Carlino et al. (2016) Somma et al. (2019)	Raman (1928) Grattan and Sun (2000) Tyler et al. (2009) Briggs et al. (2011)
Sagnac	Rotation		Rotational sensor	Hawaii Etna, Stromboli	High frequency	Wassermann et al. (2020) Eibl et al. (2022) Wassermann et al. (2022)	Sagnac (1913a, b)

BOFDA: Brillouin Optical Frequency Domain Analysis
 BOFDR: Brillouin Optical Frequency Domain Analysis
 BOTDR: Brillouin Optical Time Domain Reflectometry
 CP- ϕ -OTDR: Chirped-pulse Phase OTDR
 DAS: Distributed Acoustic Sensing
 DDSS: Distributed Dynamic Strain Sensing
 DVS: Distributed Vibration Sensing ϕ -OTDR: Phase OTDR
 OTDR: Optical Time Domain Reflectometry
 OFDR: Optical Frequency Domain Reflectometry
 ROTDR: Raman Optical Time Domain Reflectometry
 ROFDR: Raman Optical Frequency Domain Reflectometry
 WS-OTDR: Wavelength Scanning OTDR

2.1 Analysis of Strain

The description of ground motion includes translation, rotation and strain components (Aki and Richards 2002). This can be understood by analyzing the transformation of a body subjected to an external force (Müller 2007; Schmelzbach et al. 2018). Let us consider a Cartesian referential system with x, y and z as the coordinate axes, and two close positions $P(x, y, z)$ and $Q(x + \Delta x, y + \Delta y, z + \Delta z)$ within the body on which a force is applied. The initial distance between points P and Q is denoted $PQ(\Delta x, \Delta y, \Delta z)$. Following the application of the force, point P moves to P' by the displacement vector $\mathbf{u}(u_x, u_y, u_z)$ and point Q moves to Q' by a displacement $\mathbf{u} + \Delta \mathbf{u}$.

In the linear theory of continuum mechanics, the transformation $PQ \rightarrow P'Q'$ is assumed to be linear. The components of the vector $\Delta \mathbf{u}$ can thus be written as

$$\Delta u_x = \frac{\partial u_x}{\partial x} \Delta x + \frac{\partial u_x}{\partial y} \Delta y + \frac{\partial u_x}{\partial z} \Delta z + O(u_x^2),$$

$$\Delta u_y = \frac{\partial u_y}{\partial x} \Delta x + \frac{\partial u_y}{\partial y} \Delta y + \frac{\partial u_y}{\partial z} \Delta z + O(u_y^2),$$

$$\Delta u_z = \frac{\partial u_z}{\partial x} \Delta x + \frac{\partial u_z}{\partial y} \Delta y + \frac{\partial u_z}{\partial z} \Delta z + O(u_z^2),$$

where we neglect, as indicated by the sign $O(\cdot)$, the second (and higher) order terms of the transformation. ∂ denotes the partial derivative operator. The transformation can be expressed in a matrix form $\left(\frac{\partial u_i}{\partial x_j}\right)$, where we use the Einstein summation convention on indices i and j , which can represent x, y or z . This matrix describes the gradient of the displacement at all points of a continuous medium. By decomposing

$$\frac{\partial u_i}{\partial x_j} = \frac{1}{2} \left(\frac{\partial u_i}{\partial x_j} + \frac{\partial u_j}{\partial x_i} \right) + \frac{1}{2} \left(\frac{\partial u_i}{\partial x_j} - \frac{\partial u_j}{\partial x_i} \right),$$

we find the first term to be strain (symmetric matrix) and the second term rotation (antisymmetric matrix), by definition. Therefore, one

can generally express the transformation $PQ \rightarrow P'Q'$ as a combination of

- a translation $\mathbf{u}(u_x, u_y, u_z)$;
- a strain $\boldsymbol{\varepsilon}$, which can be seen as the change of length of lines, and is defined by the tensor

$$\boldsymbol{\varepsilon} = \begin{pmatrix} \varepsilon_x & \gamma_{xy} & \gamma_{xz} \\ \gamma_{yx} & \varepsilon_y & \gamma_{yz} \\ \gamma_{zx} & \gamma_{zy} & \varepsilon_z \end{pmatrix},$$

in which the components are expressed by

$$\varepsilon_x = \frac{\partial u_x}{\partial x}, \varepsilon_y = \frac{\partial u_y}{\partial y}, \varepsilon_z = \frac{\partial u_z}{\partial z},$$

$$\gamma_{xy} = \gamma_{yx} = \frac{1}{2} \left(\frac{\partial u_x}{\partial y} + \frac{\partial u_y}{\partial x} \right),$$

$$\gamma_{xz} = \gamma_{zx} = \frac{1}{2} \left(\frac{\partial u_x}{\partial z} + \frac{\partial u_z}{\partial x} \right),$$

$$\gamma_{yz} = \gamma_{zy} = \frac{1}{2} \left(\frac{\partial u_y}{\partial z} + \frac{\partial u_z}{\partial y} \right);$$

- and a rotation of the whole region (including P and Q), defined by a tensor

$$\boldsymbol{\Omega} = \begin{pmatrix} 0 & \omega_{xy} & \omega_{xz} \\ \omega_{yx} & 0 & \omega_{yz} \\ \omega_{zx} & \omega_{zy} & 0 \end{pmatrix},$$

in which the components are expressed by

$$\omega_{xy} = -\omega_{yx} = \frac{1}{2} \left(\frac{\partial u_x}{\partial y} - \frac{\partial u_y}{\partial x} \right),$$

$$\omega_{xz} = -\omega_{zx} = \frac{1}{2} \left(\frac{\partial u_x}{\partial z} - \frac{\partial u_z}{\partial x} \right),$$

$$\omega_{yz} = -\omega_{zy} = \frac{1}{2} \left(\frac{\partial u_y}{\partial z} - \frac{\partial u_z}{\partial y} \right).$$

Rotation is sometimes expressed as a pseudo-vector

$$\boldsymbol{\Omega}_v = \begin{bmatrix} \Omega_x \\ \Omega_y \\ \Omega_z \end{bmatrix} = \begin{bmatrix} -\omega_{yz} \\ \omega_{xz} \\ -\omega_{xy} \end{bmatrix} = \begin{bmatrix} \omega_{zy} \\ \omega_{xz} \\ \omega_{yx} \end{bmatrix}.$$

The three elements (translation, strain and rotation) are at the basis of the description of ground motion by the equation of motion (Aki and Richards 2002; Müller 2007; Schmeltzbach et al. 2018), from which ground deformation and seismology originate from.

Global Navigation Satellite System (GNSS) measures ground displacement, and has been successful on many volcanoes (e.g., Palano et al. 2023). Its relative resolution is limited to several millimeters over distances of kilometers. Applications of GNSS focus on large ground motions (larger than few millimeters) occurring over long term (days to months). Seismometers measure ground velocity or acceleration in the micrometer/second range, and form the basis of monitoring networks at many volcanoes. Broadband seismometers measure the three components of the seismic wave field over a typical range of 0.01–100 Hz. However, they are also sensitive to changes in the tilt of the instrument, as noted by Rodgers (1968). Tiltmeters can record long-term ground tilt (e.g., Gambino and Cammarata 2017). In conventional seismology and volcano-seismology, the rotational components have been disregarded because they were thought to be sufficiently small (Bouchon and Aki 1982). Until recently, portable instruments capable of detecting rotational components were not available, making direct measurement of rotation difficult. Strainmeters are designed to measure the strain field (Gladwin and Hart 1985; Agnew 1986). However, they often only measure certain components of the strain tensor, such as single axial components (Zumberge et al. 1988; DeWolf et al. 2015; Hatfield et al. 2022), volumetric strain (Linde and Sacks 1995; Bonaccorso et al. 2016; Canitano et al. 2021) or 3-components of the strain tensor (Maccioni et al. 2019). The volumetric strain ($\varepsilon_x + \varepsilon_y + \varepsilon_z$) can be accurately measured by dilatometers in boreholes (Sacks et al. 1971). These instruments provide a better understanding of volcano deformation processes at low amplitude and low frequencies (Linde and Sacks 1995; Currenti and Bonaccorso 2019). Studies have investigated higher frequencies of strain (>0.1 Hz, e.g., seismic frequencies)

and co-seismic strain changes associated with seismic events have been investigated in mines (McGarr et al. 1982; Ogasawara et al. 2005). Although some strain measurements exist on certain volcanoes, there are very few publications reporting volcanic strain at high frequencies (e.g., Di Lieto et al. 2020).

The description and interpretation of volcano-seismic wave fields have mainly been conducted using truncated observations of the ground motion. These observations only consider the translational components, neglecting both rotation and high-frequency strain. Volcanic processes generate a large variety of seismic signals, including volcano-tectonic events (VT, 3–40 Hz), long period events (LP, 0.2–5 Hz), very-long period signals (VLP, 0.05–0.2 Hz), tremor (~ 0.1 –10 Hz), and volcano-explosive signals (VEQ, explosion quakes, ~ 1 –10 Hz). Therefore, it is necessary to further explore the volcanological signatures of rotation and strain.

The development of fiber optic instruments provides new opportunities to access to the full wave field over a wide range of frequencies, enabling a more complete description of volcanic events and a better understanding of their nature. Figure 1 shows several portable instruments that use fiber optic technologies, allowing for the measurement of components of the full seismic wave field. The following section describes methods for sensing the translational, strain and rotational components of the seismic wave field at a point, followed by methods for distributed sensing of strain and temperature.

2.2 Fiber Optic Point Sensing

2.2.1 Seismometer and Strainmeter Point Sensing: The Fabry–Perot Interferometer

The Fabry–Perot interferometer is an optical cavity composed of two parallel light reflectors. It was designed by Perot and Fabry (1899) and has since then been utilized in numerous fiber optic point sensing devices to measure strain variation (Nur et al. 2016). The cavity can be



Fig. 1 Pictures of several sensors using fiber optic sensing. BOTDR stands for Brillouin Optical Time Domain Reflectometry and DDSS stands for Distributed Dynamic Strain Sensing. These techniques are explained in detail in Sect. 2.3. **a** Various seismic sensors: the optical sensor contains a micro-opto-mechanical cavity on a fiber tip (Pisco et al. 2018). Note the smaller size of the optical sensor as compared to other conventional sensors (picture from Pisco et al. 2018, supplementary information). **b** Rotational sensor and broadband seismometer deployed at Etna volcano (Eibl et al. 2022) (Picture: E. Eibl, U. Potsdam). **c** iDAS and Carina interrogators deployed at Pizzi Deneri observatory at Etna volcano in July 2019 (Picture: P. Jousset, GFZ). **d** Deployment of

a fiber in a trench of about 30 cm depth at Etna volcano in July 2019 (Picture: M. Weber, GFZ). **e** Standard telecom cable (~0.5 cm diameter) deployed in the trench (Picture: P. Jousset, GFZ). **f** Various Distributed Fiber Optic Sensing interrogators in the framework of the Focus Project (Gutscher et al. 2019, 2023): a BOTDR interrogator G1-R (Febus); a BOTDR (T-BERD) interrogator (Viavi); an iDAS interrogator (Silixa). Each of these interrogators is connected to a different fiber within a submarine cable of about 30 km length, belonging to the infrastructure from the European Multidisciplinary Seafloor and water column Observatory and from the Istituto Nazionale di Fisica Nucleare - Laboratori Nazionali del Sud (Italy—Sicily)

between 0.1 and 1 mm in length and allows light to enter only when it resonates with the cavity. The resonance of the cavity enables the measurement of the light wavelength, or alternatively, when the cavity deforms, the resonance frequency changes for a fixed light wavelength. Instruments that use this principle include seismometers (Pechstedt and Jackson 1995; Pisco et al. 2018; Feron et al. 2020), tiltmeters (Chawah et al. 2015) and strainmeters (Ferraro and De Natale 2002; Coutant et al. 2015; Bernard et al. 2022).

For instance, Feron et al. (2020) developed an optical seismometer that utilizes Fabry–Perot interferometry. The EW, NS and vertical components rely on the distance between the end of a glass fiber that emits infrared laser light and a reflecting mirror on the mobile mass of a passive geophone (Seat et al. 2012). The space between the mirror and the glass fiber is the optical cavity, i.e., the Fabry–Perot interferometer. Coutant et al. (2015) developed a strainmeter that utilises a series of Fabry–Perot cavities (~1 cm long) and a high-performing spectrometer to measure strain with great sensitivity over a large frequency band. The system has the advantage of being able to be interrogated at a long distance from the sensor via standard fiber optic cable. The sensor can be set up in a harsh environment, such as an active fumarole field, while the electronics can be located in a safer location. This ensures a longer life for the monitoring system.

2.2.2 Rotational Sensors (Sagnac Effect)

To measure the rotational component of the wave field, the so-called “Sagnac effect” is used (Sagnac 1913a, b), although its full understanding is still under discussion (Bhadra et al. 2022; Gautier et al. 2022). The technique involves an interferometer which analyses the light sent around a closed loop of a fiber optic cable (beams) mounted on a rotating platform. As the platform rotates, the interference fringes are displaced from their initial positions (when the platform is not rotating). Sagnac (1913a, b) determined that the phase shift $\Delta\Phi_S$ of the

interference fringes as being proportional to the rotation rate vector $\dot{\Omega}_v$ of the platform:

$$\Delta\Phi_S \approx \frac{8\pi A}{\lambda c} \vec{n} \cdot \dot{\Omega}_v,$$

where A is the area of the loop oriented by $\vec{n}$, λ is the light wavelength and c is the speed of light in vacuum. The phase difference is determined by multiplying the difference in travel times by the optical frequency c/λ , as stated by Lefèvre (2014).

Ground rotations were initially measured in laboratory conditions using records of artificial explosion signals (Nigbor 1994) or large earthquakes (Igel et al. 2005). The development of portable rotational sensors has provided opportunities to gain a better understand of the composition of the seismic wave field from volcanic earthquakes. Rotational sensors measure the rotation directly, and hence also tilt of the ground. They are not sensitive to translational ground motion, as noted by Bernauer et al. (2012) and Kislov and Gravrov (2021). The seismic wave field consists of different phases, including body waves (P- and S-waves) and surface waves (Love and Rayleigh waves) (Aki and Richards 2002). In a homogeneous medium, P-waves do not cause rotation. S-waves can be divided into polarized S-waves, and we refer to these as SH and SV waves, respectively. A three-component seismometer can detect all these phases. Volcano-tectonic earthquakes (VT) are generally triggered by the rupture of faults, which can be approximated by a double-couple source mechanism. As with tectonic earthquakes outside volcanic areas, P-waves are followed by S-waves and by surface waves, such as Rayleigh and Love waves. However, long-period events (LP) or long-lasting tremors have been explained by various source mechanisms. For example, resonance of fluid-filled fractures (Chouet 1996) or of the volcanic conduit (Neuberg 2000; Jousset et al. 2003, 2004), slow deformation processes (Bean et al. 2014), or fluid flow (Julian 1994; Hellweg 2000; Rust et al. 2008). The translational components from seismometer records may present challenges in

distinguishing various seismic phases for LP events due to emergent and overlapping signals. For instance, it may be challenging to distinguish between P-waves polarized parallel to the propagation direction from S-waves polarized perpendicular to the propagation direction and the different surface wave types. However, a rotational sensor can be used to directly identify the wave field composition of LP events or tremor. For a rotation sensor located at the free surface of a semi-infinite homogeneous medium, the vertical component is sensitive only to SH and Love waves, whereas its horizontal components are sensitive to SV waves or Rayleigh waves (Sollberger et al. 2018). As a first approximation, if the rotational sensor displays a signal in its vertical component only, then this signal represents a wave field which is dominated by SH waves, neglecting topography and subsurface structures.

The six-component (6-C) ground motion, consisting of three translational and three rotational motion components (see Fig. 2), enables

the derivation of ground properties from dispersion curves. Additionally, it provides information, including back azimuth (direction measured from north to direction of the incoming waves), phase velocities, and wave types, on transient signals such as earthquakes or tremor. One way to study transient signals is to estimate the back azimuth by using the similarity of the horizontal components of the rotational sensor (Wassermann et al. 2020; Yuan et al. 2020). Another approach involves using the similarity of the vertical rotation rate and the transverse acceleration to derive the back azimuth and phase velocity of the arriving waves (Hadziioannou et al. 2012; Wassermann et al. 2016). In theory, back azimuth estimation can be performed without any frequency constraint. However, at higher frequencies, the wave field may be affected by scattering of the seismic waves in the ground, which can result in less reliable back azimuth estimation compared to those obtained at lower frequencies. Additionally, the 6-C setup enables correction

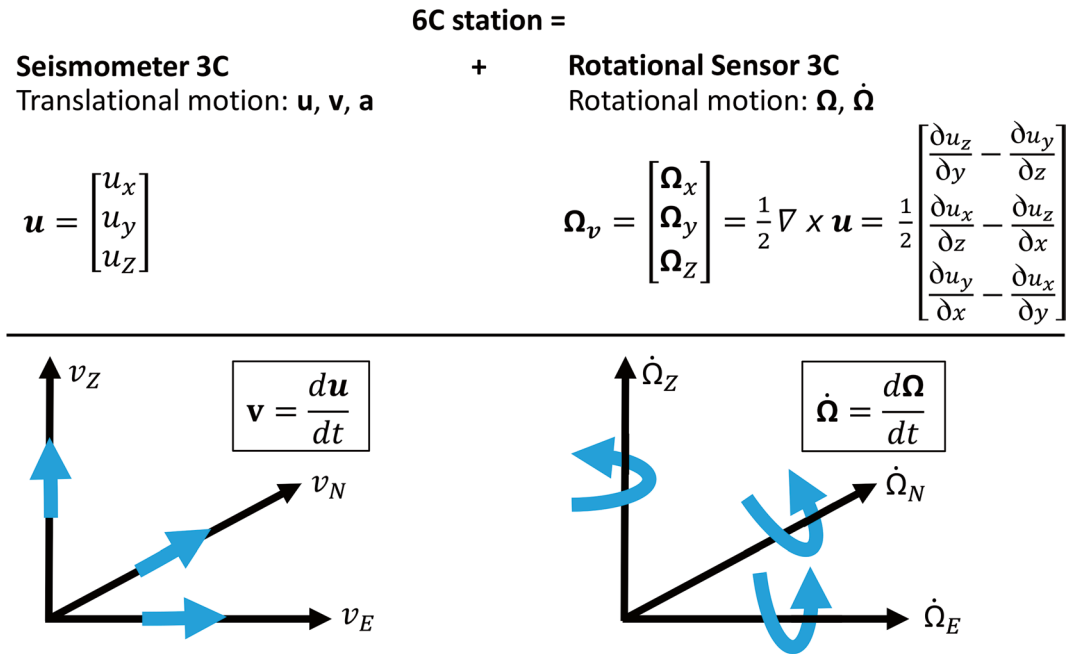


Fig. 2 Definition of a 6C station composed of a co-located seismometer and rotational sensor. For notation see equations in Sect. 2.1. $\mathbf{u}, \mathbf{v}, \mathbf{a}$ stands for displacement,

velocity and acceleration, respectively; Ω and $\dot{\Omega}$ are rotation and rotation rate, respectively; $\times$ is the curl operator

of the seismometer data for tilt contamination (Bernauer et al. 2020).

In 2018, Wassermann et al. (2020) deployed various sensors, including a rotational sensor, seismometers, accelerometers and tiltmeters, during the eruption at Kilauea volcano in Hawaii. They recorded three Mw 5 earthquakes and identified clear coseismic-rotation steps (offset in the value of the rotation measurement) in 3D (Wassermann et al. 2020). Wassermann et al. (2022) deployed three rotational sensors on Stromboli volcano, Italy. This allowed for the description of the wave field, which was composed of SV- and SH-type waves. The location of seismic events was determined using waveform similarity and a new class of volcanic events caused by jetting was detected. Eibl et al. (2022) conducted a study on translational and rotational sensor records at Etna volcano, Italy. The study aimed to evaluate the performance of a rotational sensor in comparison to a co-located seismometer and the INGV network concerning the detection and location of tremor and LP and VT events together with wave field characterization (see Sect. 3.2 of this chapter).

2.3 Distributed Fiber Optic Sensing (DFOS)

2.3.1 Fundamental Concepts

Distributed Fiber Optic Sensing (DFOS) enables simultaneous strain (or strain rate) measurement at thousands of points using an unmodified optical fiber as the sensing element (Parker et al. 2014). The term “Distributed Fiber Optic Sensing” encompasses many techniques (Nickès and Ravet 2010; Masoudi et al. 2013; Masoudi and Newson 2016, 2017), all resulting in distributed measurements along the fiber (Table 1). The fundamental principle of DFOS involves an optical fiber connected to an interrogator. The interrogator comprises a laser that shoots light within the fiber and a system that analyses the modified properties of the light after its interaction with the glass (e.g., through scattering). The laser emits infrared light pulses, typically lasting a few nanoseconds, which propagate

in the forward direction (interrogator towards fiber). The light scatters in all directions along the fiber and part of the scattered light then propagates backward towards the interrogator. A photo detector, also located in the interrogator detects the backscattered light, where it is also analyzed. Environmental parameters such as temperature, strain, pressure, and force can influence the properties of the backscattered light. The fiber serves as both the carrier of the light and as the sensing elements. Interrogation methods can be conducted in either the time domain, using incoherent or coherent light pulses, or in the frequency domain, such as with swept wavelength interferometry.

The quantities typically measured for each emitted pulse include

- the time of flight, which is the travel time between the laser emitting the light pulse and its return to the photo detector;
- the amplitude of the backscattered light;
- the frequency or the phase of the backscattered light.

Various sensing techniques are being developed that use different

- scattering processes of the light within the optical fiber, such as Rayleigh, Brillouin and Raman (see below);
- type of light sent (coherent or incoherent light, pulses or frequency sweep);
- fiber structure, which determines how the light propagates in the fiber. The core diameter defines whether the fiber is so called “single mode” or “multi-mode”. Fibers can be “standard” (e.g., telecom fiber) or “engineered” to enhance light interactions with the glass for increased sensitivity.

To perform the measurement for time domain approaches, pulses are sent successively at a frequency of several kHz. When a pulse of light is sent, at any time, it spans a certain section of the fiber, over which the measurement is performed. Fast processing and analysis of the light amplitude and phase is conducted computationally

after analog-to-digital conversion. The details of the complex processing on the light properties (phase and amplitude, stacking and filtering processing) depend on the interrogator. The outcome is a set of measurements distributed along the fiber, which provides information on various environmental parameters, such as axial strain and temperature probed over the gauge length. The acquired data, which can be extensive depending on the sampling rate (spatial and temporal) and the length of the probed fiber, is saved on a hard drive also located in or near the interrogator.

2.3.2 Scattering of Light with the Fiber Glass Structure

When light is transmitted through an optical fiber in the forward direction, it interacts with the glass through scattering processes. The scattered light then propagates in the opposite direction (backward) until it reaches the photo detector. The wavelength of the incident source affects light scattering, which is also influenced by various parameters such as the size, shape, concentration and refractive index of the scattering particles. Irregular surfaces, even at the molecular level, can cause light to scatter in random directions. In optical glass fiber, the scattering of light is caused by compositional fluctuations, such as molecular level irregularities, in the glass structure, as noted by Archibald and Bennett (1978). Fluctuations in the fiber structure are caused by variations in glass density and compositional inhomogeneities. These are naturally acquired and frozen in the structure of the fiber during its fabrication process as the temperature decreases from the glass softening temperature (a few hundred degrees) to room temperature (Lu et al. 2019). Figure 3 shows the frequency spectrum of the scattered light which typically involves three main scattering processes: Rayleigh, Brillouin and Raman scatterings.

Rayleigh scattering is an elastic process that does not alter the frequency of light.

Brillouin and Raman scattering are inelastic processes that cause shifts in the frequency of light (Bao and Chen 2012; Lu et al. 2019).

According to quantum mechanics, microscopic vibrations in solid media are quantized, meaning that vibration energy is exchanged in the form of so-called “phonons”. Phonons are collective excitations in a periodic, elastic arrangement of atoms or molecules which are condensed specifically in solids and some liquids. In simple terms, a phonon is a discrete unit of vibrational mechanical energy. It is calculated by multiplying the phonon frequency by the Planck’s constant. Various vibration modes exist, each with different frequencies and thus phonon energies:

- Acoustic phonons are linked to long-wavelength vibrations, where neighboring particles oscillate almost in phase. They have relatively low frequencies, for example, in the gigahertz region;
- Optical phonons are linked to vibrations where neighboring particles oscillate almost in anti-phase. The frequencies of optical phonons are in the terahertz region, resulting in significantly higher phonon energies than those of acoustic phonons.

Phonons participate in both Brillouin scattering, which involves acoustic phonons, and Raman scattering, which involves optical phonons. In Raman scattering, an incident photon is converted into a photon with slightly lower energy, and a phonon carries away the difference in photon energies.

When a pulse of light is transmitted through the fiber, all scattering processes occur simultaneously. Each process is addressed using different instruments, resulting in numerous techniques and acronyms.

Optical Time Domain Reflectometry (OTDR), Rayleigh Scattering

In 1881, Lord Rayleigh demonstrated (Rayleigh 1881) that light propagating in a medium is scattered by small particles within the medium, up to about a tenth of the wavelength of the light. The color blue to the sky is due to Rayleigh scattering off the molecules of the atmosphere. Rayleigh scattering in optical fibers is typically

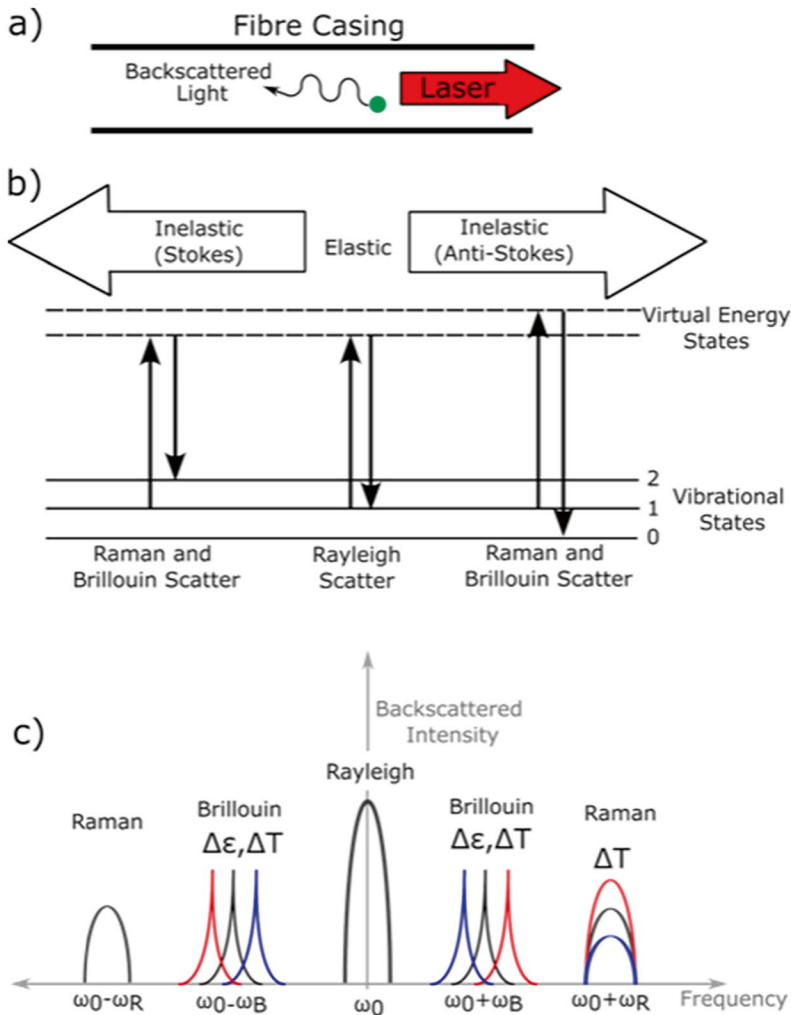


Fig. 3 Distributed Fiber Optic Sensing (DFOS) techniques are based on sending coherent pulses at one end of the fiber and analyzing the backscattered light, after it has interacted with the fiber glass structure. **a** An example of light backscattered by an inhomogeneity in the fiber optic cable. **b** A schematic of the evolution of the energy state of the molecule/atom causing the backscattered light depicted in subplot **a**. Rayleigh scattering is an elastic process where the scattered energy equals the incidence energy of the laser. Brillouin and Raman scattering are inelastic processes that alter the vibration state of the atom or molecule in the fiber in two different ways. When the backscattered light has a lower frequency than the incident light, the medium has absorbed

some of the light energy. This is referred to as the Stokes process. Conversely, when higher frequency light is emitted relative to the incident light, the medium has released some energy. This is referred to as the anti-Stokes process (Hartog 2017). **c** A summary of the expected location of the Rayleigh, Brillouin, and Raman spectra relative to the frequency ω_0 of the incident light (Muanenda et al. 2019). The Brillouin peaks shift from the original frequency toward higher frequencies with increasing temperature and strain (red line) and towards lower frequencies with decreasing strain/temperature (blue line). Only the anti-Stokes Raman spectra displays a variation in peak intensity with changing temperature, i.e., increasing (red line) or decreasing (blue line) temperature

caused by refractive index fluctuations within the glass along the fiber. Rayleigh scattering results in a spectral broadening of the incident light without any frequency shift, which is an elastic scattering process. In a fiber glass, this principle is used to measure the time of flight, which is the time interval between emitting the light from the laser and observing the backscattered light at the photo detector. The distance d along the fiber can be calculated using the formula

$$d = \frac{c}{2n}t,$$

where t is the backscattered detection time, c is the speed of light in vacuum, n the average refractive index along the fiber; the factor 2 comes from the forward and backward travel of the light. The technique to measure the time of flight of the light between the interrogator and the scattering point is called Optical Time Domain Reflectometry (OTDR). As Rayleigh scattering occurs along a fiber, it is defined as a distributed fiber optic sensing method (Barnoski et al. 1977). The dynamic range in OTDR depends on the sensitivity of the equipment, including the pulse duration, pulse power, and photodiode sensitivity. A high pulse power with a wide pulse duration can increase the signal-to-noise ratio (SNR), allowing for long-distance measurements (typically tens of kilometers). However, this increase in sensitivity comes at the cost of spatial resolution, as the pulse is wider. If the power of the pulse is too high, non-linear effects may occur in the fiber, rendering the measurement irrelevant (Lu et al. 2019). Additionally, Rayleigh scattering is the primary cause of light intensity attenuation as it propagates through the glass (Personick 1983). Telecommunication companies have been using OTDR for years to find faults, such as optical loss and reflections in their networks (Philen et al. 1982). The conventional OTDR used in testing telecommunication network quality employs pulses of 10 ns which correspond to 1-m resolution, while maintaining a high dynamic range. One of the great advantages of OTDR is that it only requires access to one end

of the fiber to make measurements along the entire cable.

Distributed Dynamic Strain Sensing (DDSS), Rayleigh Scattering

Most Distributed Dynamic Strain Sensing techniques use Rayleigh (elastic) scattering (Masoudi et al. 2013) to measure the strain or strain rate of the fiber over the gauge length, which is caused by the strain in the ground transmitted to the fiber. This sensing technique is commonly referred to as “Distributed Acoustic Sensing”, although this term is inappropriate. Acoustic waves are linked to variation in pressure, which are characteristic of seismic P-waves, also known as “compression waves”. Rayleigh scattering can detect the ground strain tensor projected along the fiber direction, which is generated by any source of dynamic strain, including pressure, shear, and vibration. Therefore, DDSS can record all seismic waves, including P-, S-, and surface waves rather than just pressure or P-waves (which are sometimes incorrectly referred to as “acoustic waves” by the oil and gas industry).

Techniques for retrieving distributed information from Rayleigh scattering use various measurement methods, which differ in the type of light, light pulse length, light pulse frequency content etc. For instance, Lu et al. (2019) describe several methods including OTDR (see above), phase-sensitive OTDR (φ -OTDR), which utilizes phase changes of the scattered light, polarization-sensitive OTDR (P-OTDR), which uses changes in the light polarization, and heterodyne OTDR (H-OTDR), which employs a complex pulse (Mussot et al. 2018; Naveau et al. 2021), Optical Frequency Domain Reflectometry (OFDR), where the analysis of the light is performed in the frequency domain and not in the time domain, etc.

The phase-sensitive OTDR (ϕ -OTDR) is a highly efficient technique for observing high-frequency strain associated with seismic and volcanic events, such as earthquakes and explosions. OTDR utilizes successive light pulses with a low coherency between them. In contrast,

ϕ -OTDR is used to measure light phase changes. It is based on successive fully coherent pulses of light with a very narrow linewidth and a stable frequency laser. The coherence length of the laser light is much longer than the fiber length. The ϕ -OTDR implementation of Taylor and Lee (1993) measures the intensity resulting from the interference of light backscattered at different scattering points along the fiber as explained by Zhang et al. (2019). Using an interferometer (e.g., Mach-Zehnder interferometer, Zetie et al. 2000; Yang et al. 2003; Cai et al. 2015) the Rayleigh backscattered light's phase φ_R is continuously analyzed in time, at all locations (time of flight) along the fiber (Masoudi et al. 2013; Parker et al. 2014; Masoudi and Newson 2016, 2017). When a fiber section of length L is elongated or contracted by ΔL (due to external strain), a change in the relative positions of scatters induces a small phase change $\Delta\varphi_R$ in the backscattered light between two successive pulses. The phase change is expressed as

$$\Delta\varphi_R = \frac{4\pi n\zeta}{\lambda} \Delta L,$$

where λ is the wavelength of the light pulse, ζ is a material dependent constant around 0.78 for fiber glass (SEAFOM 2018), n is the group refractive index (usually 1.468). This equation enables the accurate retrieval of the fiber elongation/contraction using an interferometer. The measured signal is the dynamic strain rate, as the interrogator analyses changes in strain over time (Lu et al. 2019). Temperature also affects the refractive index resulting on an apparent phase change. Therefore, the resulting signal contains both strain and temperature effects that cannot be distinguished. When the strain signal has a frequency content much higher than that of temperature changes, such as in high frequencies applications in seismology, optical dispersion is neglected and the refractive index is assumed to be constant over time (Lindsey et al. 2020).

As light propagates through the fiber over long distances, its amplitude decreases due to

attenuation, which in turn reduces the signal-to-noise ratio. The attenuation of light depends on the refractive index profiles along the fiber and the material itself. Furthermore, it is necessary to ensure that the backscattered light is completely returned before shooting the next pulse to avoid interferences between successive pulses. Hence, for longer cables, the number of pulses per second need to be reduced, decreasing the bandwidth. The strain rate resolution and sensitivity are therefore reduced with increasing fiber length. Increasing of the pulse duration or the gauge length has a significant impact on overall sensitivity and range of interrogation, but at the expense of the spatial resolution. Artificial discontinuities in the refractive index distribution can be introduced in so called "engineered fibers" to increase the signal-to-noise ratio (Shatalin et al. 2021). The benefits of using engineered fibers over standard telecom fibers were illustrated at Etna volcano (Diaz-Meza et al. 2023).

Distributed Dynamic Strain Sensing (DDSS) is well-suited for monitoring strain changes associated with the seismic wave field. It provides more accurate results on single-mode fibers, although experiments have been successfully carried out with multi-mode fibers (Chen et al. 2018; Jousset et al. 2022). The method was first used in the oil and gas industry and has been adopted by the Earth Sciences community for hazard assessment, including detection and characterization of landslides (Huntley et al. 2014; Lienhart 2015; Picarelli et al. 2015; Michlmayr et al. 2017; Schenato 2017; Kogure and Okuda 2018), teleseismic earthquakes (Dou et al. 2017; Lindsey et al. 2017; Jousset et al. 2018; Wuestefeld et al. 2023), volcano-tectonic earthquakes (Jousset et al. 2018; Nishimura et al. 2021), volcanic long-period events (Currenti et al. 2021), volcanic very long period signals (Currenti et al. 2023), volcanic tremor (Fichtner et al. 2022; Jousset et al. 2022) and volcanic explosive activity (Currenti et al. 2021; Jousset et al. 2022).

Distributed Strain and Temperature Sensing (DSS), Brillouin Scattering

Brillouin (1914) predicted light scattering from propagating acoustic phonons (see definition earlier). Acoustic waves that are thermally excited create periodic density waves, resulting in changes in the refractive index of the fiber glass. This process causes a frequency shift of the scattered light, which depends on the velocity of the sound wave. Measurable parameters in a Brillouin scattering spectrum comprise the Brillouin frequency ν_B , the Brillouin spectrum linewidth, and the Brillouin intensity (Lu et al. 2019). The measurement involves stacking records from successive pulses over integration time ranges of several seconds to minutes. Brillouin-based distributed sensors can address both static strain and temperature over long distances, typically exceeding 10 km (Horiguchi et al. 1995; Soto and Thévenaz 2013).

BOTDR (Brillouin Optical Time Domain Reflectometry) is a technique that involves the analysis of Brillouin scatter through the use of OTDR. It is based on the detection of spontaneous Brillouin scattering light and was developed by Kurashima et al. (1990, 1993). BOTDR is de facto the most established technique for use in Earth Sciences. This method requires access to only one end of a fiber, as conventional OTDR. The location of the strain/temperature change along the cable can be determined simultaneously using Rayleigh scattering (with OTDR). BOTDR involves the interaction of the light with fiber properties that are sensitive to strain and temperature. The Brillouin frequency shift increases in proportion to the temperature or strain induced in the fiber. The change in strain $\Delta\varepsilon$ and/or temperature ΔT that the fiber experiences relative to the initial recording can be expressed as:

$$\Delta\nu_B = \Delta\varepsilon C_\varepsilon + \Delta T C_T,$$

where $\Delta\nu_B$ represents the change in Brillouin frequency observed at two different recording times. The strain coefficient C_ε and the temperature coefficient C_T range from 0.04 – 0.05 MHz/ $\mu\epsilon$ and 1.08 – 1.26 MHz/ $^\circ\text{C}$ respectively (Bao

and Chen 2012; Galindez-Jamioy and López-Higuera 2012), depending on the fiber type (Lu et al. 2019). The change in frequency is caused by a linear change on the cable to the external strain tensor projected along the fiber (Horiguchi et al. 1989) and/or in temperature (Kurashima et al. 1990). One significant advantage of BOTDR is that measurements using the same fiber can be performed independently at two different times (weeks or months), yet the difference between the two measurements remains valid. Although several improvements have been attempted (Chow et al. 2018), BOTDR remains less sensitive than DDSS (Bao and Chen 2012). The spatial resolution depends on the pulse width (Thévenaz 2010). Typically, BOTDR sensing range spans 1 to 100 km, with a spatial resolution from 0.2 to 100 m, a temperature accuracy from 0.37 to 5 $^\circ\text{C}$ and a strain accuracy from 7.4 to 100 $\mu\epsilon$. Some recent instrument providers claim a strain accuracy of 1 $\mu\epsilon$.

BOTDR has various applications, including structural health monitoring (Ohno et al. 2001), studies on gravitational instabilities (Sun et al. 2016), submarine faults (Gutscher et al. 2019) and sinkhole detection and monitoring (Linker and Klar 2017). Zhang et al. (2018) have successfully converted strain to displacement in the case of a field shear test where the orientation and width of the shear zone relative to the cable, as well as the cable coupling, were known a priori. Like DDSS, distributed strain sensing (DSS) is highly dependent on cable coupling with the surrounding media. Geotechnical pull-out tests have demonstrated that there are three degrees of cable coupling, dependent on the amount of shearing: elastic (fully coupled), elastoplastic (partially coupled) and purely plastic (decoupled) (Zhang et al. 2016). Different strain–displacement relationships have been developed based on the degree of cable coupling (Zhang et al. 2018). Initial laboratory tests indicate that block and tube anchors on fiber cables increase cable-sediment coupling (Wu et al. 2020). However, further experimental studies are required in order to better understand their effect on both coupling and observed strain distribution.

BOTDR is based on spontaneous Brillouin scattering which involves analyzing backscattered light. An alternative approach is to use stimulated Brillouin scattering whereby two light sources propagating in opposite directions cause a stimulated Brillouin scattering along the cable (Bao and Chen 2012; Bao et al. 2021; Lu et al. 2019). The interaction of the two wave types travelling in opposite directions creates acoustic waves through electrostriction. This phenomenon is utilized in a number of distributed techniques using various types of light signals at either end of the fiber, leading to enhanced Brillouin scatter (Hartog 2017). For instance, Brillouin Optical Time Domain Analysis (BOTDA) involves shooting a pulse and continuous wave into the fiber at both ends. Brillouin optical frequency-domain analysis (BOFDR) operates similarly, but with the pulsed signal substituted with a frequency modulated continuous wave (Horiguchi et al. 1989). The advantage of these techniques is that they provide rapid temperature and strain sensing at high resolution along the cable (Hartog 2002; Culshaw 2004; Ravet 2011; Bernini et al. 2012). However, the disadvantage is that access to both ends of the fiber is required and should the cable be cut, measurements are no longer possible. Brillouin optical coherence domain analysis (BOCDA) involves shooting frequency modulated light waves at either end of the fiber and using the correlation of the two signals within the fiber to observe Brillouin scatter at a precise location along the cable (Hasegawa and Hotate 1999; Song and Hotate 2007). This technique can provide millimeter-scale resolution rapidly at specific locations. However, scanning the entire cable can take longer compared to other distributed techniques, such as BOTDA and BOFDR. Like for BOTDA and BOFDR, access to both ends of the cable is required.

Experiments in Geosciences have primarily focused on landslide environments (Sun et al. 2016, 2022), where fibers are deployed specifically to cross high strain deformation zones. This indicates the potential for studying deformation over large spatial scales in volcanic settings. A BOTDR experiment is currently

underway in the eastern region of Etna volcano beneath the Ionian Sea. The aim is to detect strain associated with fault movement and its link to Etna's volcanic activity (Gutscher et al. 2019; see also Sect. 3 of this chapter).

Distributed Temperature Sensing (DTS), Raman Scattering

Chandrasekhara Venkata Raman first reported Raman (inelastic) scattering in 1928 (Raman 1928). This scattering process occurs when photons interact with the natural high frequency vibrations of bonds between atoms or molecules in the fiber glass. The scattered photons are emitted in a different frequency spectrum than that of the initial light. Distributed Raman measurement systems can use either time-domain or frequency domain techniques to extract distributed information. Distributed Temperature Sensing (DTS) is a type of distributed sensing based on Raman scattering that address temperature sensing through the measurement of the light property variations, and without sensitivity to strain (Watson et al. 1981). Temperature changes affect the Raman spectrum in three ways: Raman frequency shift, intensity and peak width (Lu et al. 2019). Only the anti-Stokes Raman spectra exhibit a variation in peak intensity relative to temperature changes (Fig. 3). Therefore, comparing the ratio of the anti-Stokes and Stokes intensities provides a measure of the temperature (Ukil et al. 2011). The resolution and distance measured depend on the laser power used. However, if the power used is too high, accurate measurements cannot be obtained, due to interference between the laser light source and the Raman scattered light. Long distance measurements above a certain power of laser light are hindered by this issue. For example, a 10 km fiber can be measured with a maximum power threshold of about 3W (Lu et al. 2019). Achieving better temperature resolution necessitates a longer measurement time, typically ranging from minutes to hours. The most commonly used technique is Raman OTDR. Commercially available DTS systems usually provide spatial resolutions of 1-m or

less, utilizing a laser with a light pulse width of 10 ns or less. DTS has a better resolution when light is transmitted in multimode fibers. For example, Liu et al. (2018) designed a dedicated fiber and resolve 1 °C temperature with a spatial resolution of 1.13 m at a distance of 25 km, and average measurement of 90 s.

DTS finds most of its applications in ground water temperature projects, such as coal, oil and gas, and geothermic studies. There are few examples of DTS applications in volcanology, such as at Mount Erebus, Antarctica (Curtis and Kyle 2011), at Campi Flegrei (Southern Italy) with submarine temperature profiling (Carlino et al. 2016) and borehole temperature monitoring (Somma et al. 2019).

2.3.3 Gauge Length, Instrumental Response and Limitations

Gauge length and spatial sampling

DFOS provides a quasi-continuous spatial profile of strain measurements along the optical fiber, spanning several tens of kilometers. The sensing section of the fiber is defined by the length of the pulse launched in the fiber, which although short in duration (a few nanoseconds), has a certain spatial length. The length of the sensing section can be adjusted by varying the duration of the pulse. The gauge length refers to the section of the fiber from which backscattered light is effectively sampled and analyzed in terms of intensity, frequency or/and phase. The integrated value of temperature and/ strain is typically allocated to the midpoint of the gauge length along the fiber (Dean et al. 2016). As time passes, the pulse propagates and another section of the fiber is probed and allocated to the middle point of that section. For any given gauge length, the spatial sampling refers to the distance between the midpoints, where the measurement over a gauge length is recorded. Therefore, each measurement covers a gauge length and is not a single point measurement. The analysis of the successive spatial sections may overlap, depending on the gauge length and the required spatial

sampling for the records. Independent records are separated by a distance equivalent to at least one gauge length. The sensitivity of each measurement decreases as the gauge length becomes shorter. The user can choose the spatial sampling (SS) and the gauge length (GL) depending on the objective of the study. Typical values for DDSS of a ~20 km long fiber could be GL=10 m, SS=4 m resulting on 5000 records of dynamic strain per time sample. According to Jousset et al. (2018), a gauge length of 10 m is the optimal value for dynamic strain sensing in seismology studies (0.1–100 Hz).

Instrumental response, frequency range

Until 2017, the use of fiber optic sensing in geophysics was primarily focused on seismic frequencies commonly used in the oil and gas industry (>1–100 Hz). The objective was to obtain more precise measurements in boreholes, which could replace strings of geophone observations (Daley et al. 2015). The goal of these studies was to accurately define the geometrical structure of the reservoir by obtaining precise seismic phase contrasts. Recorded amplitudes are poorly constrained at low frequencies (<0.5 Hz), even in boreholes (Becker et al. 2017). DDSS instruments with cables deployed at the shallow surface of the Earth have also measured low frequencies, which expands their potential applications beyond boreholes. Examples reporting low frequencies associated to surface waves (20 s) from remote large earthquakes include the Indonesia Mw 7.4 earthquake recorded in Iceland (Jousset et al. 2018) as well as several other earthquakes, such as Alaska's Mw 7.9 (Lindsey et al. 2020), and the Turkey earthquake on 14.02.2023 (Jousset et al. 2023). At lower frequencies (below 30 s), the temperature effect increases, and may obscure low frequencies of geophysical interest.

2.3.4 Validation of Fiber Optic Rotational and Distributed Dynamic Strain Sensing

Recent technological advances have made it possible to sense rotation and dynamic strain with high spatial and temporal resolution over

a broad frequency range, using rotational sensors and Distributed Dynamic Strain Sensing. This allows for probing the full wave field. However, the application of both rotation and DDSS in seismology and volcanology is an emerging field. Therefore, many open questions arise regarding the DDSS response and the coupling between the fiber and the ground, which are strongly dependent on the fiber installation conditions.

Understanding records in detail can be challenging, especially when dealing with BOTDR, DDSS and DTS measurements. These measurements do not correspond to a single point, unlike conventional point sensors, but rather represent an integrated response over a certain distance (the gauge length). Therefore, direct comparison with point source measurements is not simple. Preliminary experiments were conducted to validate DDSS measurements by comparing them with indirect strain estimates from co-located or nearby conventional sensors, such as geophones and broadband seismometers (Daley et al. 2015; Bona et al. 2017; Jousset et al. 2018; Wang et al. 2018; Yu et al. 2019; Lindsey et al. 2020). Estimates of strain and rotational fields can be obtained indirectly by using conventional sensors that are adequately deployed to reproduce displacement gradients (Oliveira and Bolt 1989; Bodin et al. 1997; Jousset and Rohmer 2012; Van Renterghem et al. 2018). These estimates can then be compared with observations from the new sensors. Estimates of strain and rotational components have been relevant in numerous seismic (Basu et al. 2013; Langston 2018) and geodetic studies, including strainmeter response and calibration (Currenti et al. 2017; Donner et al. 2017), performance of rotational seismometers (Suryanto et al. 2006), computation of strain rate maps (Shen et al. 2015), estimates of the stress field induced by the passage of seismic waves (Spudich et al. 1995), determination of seismic phase velocity (Gomberg and Agnew 1996; Spudich and Fletcher 2008) and estimates of wave attributes (Langston and Liang 2008). In general, the methods can be grouped in two main families, relying on single or multiple station methods.

On the one hand, the single station method utilizes the property that strain rate can be derived from the ground velocity records knowing the ground phase velocity (Mikumo and Aki 1964; Jousset et al. 2018; Lindsey et al. 2020). However, determining the ground phase velocity is not straightforward and requires approximations on both the wave field and the subsurface velocity structure. This method is only relevant to seismology. It has been widely used to estimate dynamic gradient displacements, the strain tensor (Gomberg and Agnew 1996; Langston and Liang 2008) and rotational components from the translational components of a 3C seismometer. This assumes that seismic energy is carried by plane waves with known horizontal velocity in a laterally homogeneous medium.

On the other hand, multiple station procedures involve using of displacements or velocity recordings from dense arrays of at least three closely located sensors (Basu et al. 2013, 2017; Currenti et al. 2017). In this case, spatial interpolation approaches (Sandwell 1987; Paolucci and Smerzini 2008; Sandwell and Wessel 2016) or the seismo-geodetic method (Spudich et al. 1995; Shen et al. 2015; Basu et al. 2013; Langston 2018; Yuan et al. 2020) are used to process the measurements. Various interpolation schemes have been developed to derive maps of the displacement field from which gradient components can be analytically or numerically computed. In addition to geostatistical approaches, which are generally used for optimal interpolation of a discrete scalar field, several interpolation schemes have been formulated using the solutions of suitable elasticity problems (Paolucci and Smerzini 2008; Shen et al. 2015; Currenti et al. 2021). Sandwell and Wessel (2016) provide a thorough review of these latter methods. The seismo-geodetic method is based on the Taylor expansions of the displacement field of first (Spudich et al. 1995) or higher order derivatives (Basu et al. 2013; Langston 2018). Both interpolation and seismo-geodetic methods have been used for seismic dynamic and geodetic quasi-static strain estimates. The single station procedure provides strain estimates at the exact position of the sensor, while the other

two methods use sensor array measurements to derive maps of strain and rotational components at irregular grid points.

In 2019, a DDSS interrogator, a dense seismic array consisting of 26 Trillium Compact—120 s broadband seismometers and a rotational sensor were jointly deployed at Etna summit. This deployment provides a unique opportunity to observe and accurately quantify the strain and rotational ground motions generated by volcanic activity (Currenti et al. 2021; Eibl et al. 2022). The direct DDSS and rotational measurements associated with an LP event on 27 August 2021 correspond well with the indirect strain and rotation estimates derived by the dense seismic array (see Fig. 4). A similar agreement is also observed using the single station method at co-located sensors (Currenti et al. 2021; Eibl et al. 2022). Overall, there is a good agreement between the array-derived strain and DDSS measurements along the fiber optic cable. Short wavelength discrepancies correspond with fault zones, indicating the potential of DDSS for mapping local perturbations of the strain field and thus site effects due to small-scale heterogeneities in volcanic settings (Pätzelt 2023). These findings validate both the proposed methods and the accuracy of DDSS (Currenti et al. 2021), which was further confirmed by Biagioli et al. (2024) at Stromboli volcano.

3 Fiber Optic Sensing for Volcano Research

3.1 Motivation

Volcanology aims to understand the structure and processes involved in the distribution and transfer of mass and energy within a volcano. This is achieved through the interpretation of volcanic signals associated with earthquakes, deformation and fluid flows. This section illustrates the benefits of using fiber optic technologies and their ability to probe the full seismic

wave field, addressing fundamental questions in volcanology relevant to monitoring:

1. Volcano-seismology: event detection and location.

Volcanic events generate seismic waves and infrasound acoustic signals, which can be used to determine their source location. Accurately estimating the location of volcanic activity is crucial for effective volcano monitoring. Volcano-seismology seeks to comprehend volcanic processes by identifying the source mechanism of the various volcanic events using signals generated within a volcano (Chouet and Matoza 2013; Jousset et al. 2022). VT earthquakes suggest a highly stressed zone at shallow depths, associated with the ascent of magmatic bodies that may reach the ground surface. The detection and location of earthquake hypocenters depend on well-designed networks of individual seismic sensors (Toledo et al. 2020). We provide examples on land and in submarine environments using DFOS and/or rotational instrumentation, with the aim of locating the source of seismic VT and LP events.

2. Structural features imaging.

Accurately determining earthquake hypocenters is limited by poor knowledge of the seismic velocity distribution within the volcano structure (Koulakov and Shapiro 2021). Studies have shown hypocenter determination is ineffective without a proper velocity model. Numerous projects in seismology, volcanology and geothermal studies are utilizing an increasingly number of sensors, e.g., the USarray (Burdick et al. 2009), and the iMush network at Mount St Helens (Hansen et al. 2016) and in geothermal studies, e.g., the IMAGE network (Blanck et al. 2020). Fiber optic methods have also begun to contribute to seismic tomography (Biondi et al. 2023). We focus here on several examples illustrating how DFOS can determine structural features, including the location of faults and subsurface ground structure.

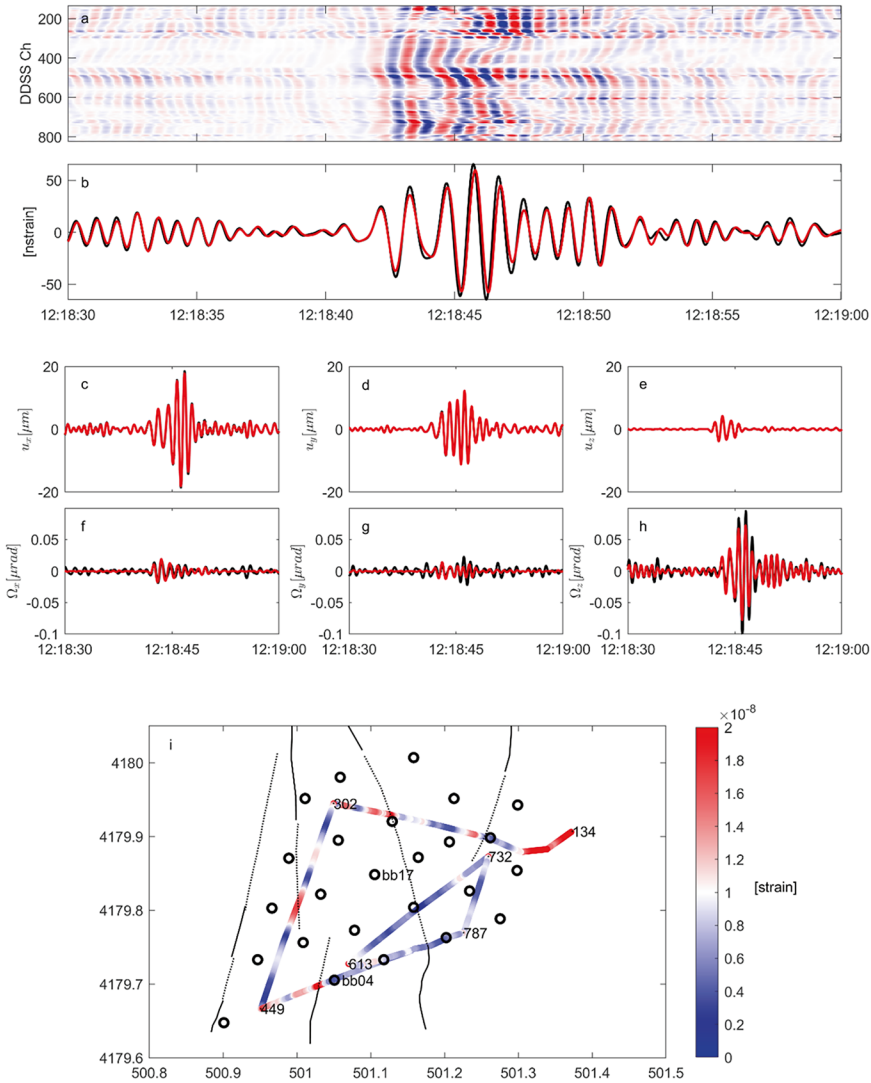


Fig. 4 Comparison between rotation and strain derived from a broadband seismic array (26 Trillium Compact 120 s sensors) and records from a rotational sensor and distributed dynamic strain sensing during a Long-Period event at Etna volcano (27 August 2019). **a** DDSS strain is obtained by integrating the DDSS strain rate records over time. Data is filtered in the frequency range 0.6–1.4 Hz. **b** Strain estimated from the seismic array using the biharmonic interpolation method (Sandwell 1987) and projected along the fiber direction (red line) and measured DDSS strain at channel 501 (black line) close to bb04. **c–e** Displacements u_x , u_y , u_z obtained by integration of the velocity components at the broadband

sensor bb17 (black line) and array derived displacements (red line). **f–h** Rotations Ω_x , Ω_y , Ω_z computed by integrating the rotation rates measured by blueSeis-3A sensor at bb17 (black) and array derived rotations (red line). In **c–h**, data at bb17 station are omitted from the interpolation computation. **i** Root Mean Square residuals between DDSS strain measurements (from panel **a**) and strain derived from the seismic array along the fiber for the LP event. Black lines and open circles indicate faults and seismometers deployed in the test area, respectively. In **i**, geographic coordinates (in km) are in the UTM33S system. The rotational sensor is located at the same location as bb17

3. Volcano dynamics.

Proper interpretation of the signatures of volcanic phenomena, such as long-term deformation, is crucial for effective monitoring. Understanding the processes that trigger these phenomena, such as gas flux in the volcanic conduit is also essential. Fiber optic technologies have been shown in several studies to improve our knowledge on volcanic processes. Here, we provide examples of two end-members in degassing processes: volcanic explosions and passive degassing. We also demonstrate how fiber optic sensing can help in understanding long-term deformation processes.

3.2 Volcano Seismology: Volcanic Events Detection and Location with Fiber Optic Methods

Active volcanoes encompass a great variety of processes, and thus generate a great variety of signals including VT earthquakes and LP events. Locating their hypocenters is fundamental for volcano monitoring, as they may indicate where stress accumulates due to magma and volcanic fluid transfer. For instance, volcano-tectonic earthquakes are typically located by measuring the arrival times of seismic P- and S-waves generated by rock rupture. To accurately locate earthquakes and determine their occurrence time, a minimum of four seismic stations is required. However, the optimal distribution of the stations for perfect earthquake location is unfortunately earthquake location dependent. An “ideal” network should then be capable of locating earthquakes at various depths and within the span of the network (Toledo et al. 2020). This is one reason why volcano-seismologists often deploy large-N networks, which cover the entire volcano. The use of DFOS offers the advantage of natural densification of observation points with a single cable, resulting in dense information of travel

times. A significant step in seismology has been achieved by the use of so-called “dark fibers”, which are unused fiber optic telecommunication infrastructures (Lindsey et al. 2017; Jousset et al. 2018). However, despite the dense distribution of records obtaining the “ideal” network for accurate earthquake locations with fiber optic cable may not be possible, depending on the cable layout. When there is no pre-existing fiber optic infrastructure, such as at most volcanoes, installation of the fiber is necessary. This can be performed at wish, e.g., for monitoring purposes, yet within the limits of the physical constraints of the volcanic site (Currenti et al. 2021; Klaasen et al. 2021; Fichtner et al. 2022; Jousset et al. 2022). There have been few reported examples of using fiber optic cables to detect and locate earthquakes in the literature (Jousset et al. 2016, 2018; Reinsch et al. 2016; Lindsey et al. 2017). Jousset et al. (2018) demonstrated that DDSS can be used on dark fiber to detect and locate a volcano-tectonic (VT) earthquake in Reykjanes, even in a not-ideal cable configuration. For other types of volcanic events, such as tremor, long-period events, pyroclastic flows, and explosions, the arrival times of the seismic waves may not be accurately determined. Therefore, other methods of event location have been developed, such as relative amplitude location methods (Jolly et al. 2002; Battaglia and Aki 2003). The amplitude method presents challenges when used with fiber optic cable due to the increased sensitivity of strain signals to local variations caused by subsurface heterogeneities, and the spatial amplitude variations generated by coupling variability of the cable (Nishimura et al. 2021). However, the spatially dense data enables the use of coherency methods, which compares the similarity of densely recorded signals (e.g., Schwarz 2019; Jousset et al. 2022). In the following, we illustrate several examples of detecting and locating volcanic long-period (LP) events using DDSS. Additionally, an example is provided on how to analyze the volcano-seismic wave field using a rotational sensor.

Seismic LP swarm analysis (Mayotte, Indian Ocean)

In May 2018, a seismic swarm began in Mayotte (Indian Ocean) accompanied by ground subsidence (Cesca et al. 2020; Lemoine et al. 2020). A year later, a new volcanic edifice, over 800 m height above the sea floor, was discovered 50 km east of the island (Feuillet et al. 2021). As of the summer of 2022, the seismic activity was still ongoing with earthquakes felt daily by the population (REVOSIMA 2021). The volcanic activity has generated various types of earthquakes, including VT, LP and VLP events. LP events occur in swarms lasting a few tens of minutes and have a frequency band between 0.5 and 6 Hz (Retailleau et al. 2022). The monitoring network consists of land seismic stations. However, strong anthropogenic noise hinders detailed analysis of the sequence of LP events. In October 2020, DDSS recordings were conducted on an existing telecommunication fiber optic cable that extends from Mayotte island towards the east at the ocean bottom (Fig. 5). The DDSS records allow for the identification of individual LP events within the swarm, except for the on-land part of the cable (0–5 km). Beyond 5 km, the cable is situated in the lagoon and then subsequently enters the ocean, where successive LP events can be more accurately identified.

Locating volcanic low-frequency earthquakes (Mt. Azuma, Japan)

Volcanic long-period (LP) earthquakes and tremor have been associated with various source mechanisms, such as volcanic fluid movement (Chouet 1996). These events are difficult to locate due to the ambiguous emergence of P- and S-wave onsets. However, seismic arrays consisting of several to tens of seismometers deployed within a small area can record correlated seismic waveforms. By measuring the arrival time differences of coherent waveforms at the array sensors, it is possible to locate LPs

and tremors. Deploying seismic arrays with a large aperture and recording seismic signals at all stations simultaneously is a challenging task. Nishimura et al. (2021) demonstrated the usefulness of DDSS records at Mt. Azuma, Japan, for locating LP events and tremor. Azuma volcano comprises andesitic edifices, including Issaikyo, Azuma-Kofuji, Higashi-Azuma, and Takayama. Volcanic activity during the Holocene period occurred around Jododaira (Fig. 6a). The fiber optic cable at Mt. Azuma extends along a winding road on the southern flank from the active craters. However, its spatial distribution is not optimal for accurate hypocenter determination (Fig. 6). To locate the hypocenters as accurately as possible, Nishimura et al. (2021) used arrival time differences and amplitudes of LPs. Each LP has a different spatial resolution. The differences in arrival time, measured for pairs of channels along the fiber cable, are related to the propagation direction of seismic waves. However, the resolution deteriorates for locations far from the cable. The amplitudes of LPs are corrected by the coda waves of regional earthquakes to evaluate the site amplification factors at each measurement point. The spatial resolution worsens in the east–west direction because the cable mainly runs in the north–south direction. To improve the spatial resolution as much as possible, the source locations are determined by minimizing residuals between observed and theoretical data for both arrival time differences and amplitudes using a grid search. The estimated locations of LPs are distributed very close to an active crater, and match well with the hypocenters determined using onset times of P- and S-waves recorded at permanent stations of Japan Meteorological Agency. This study provides evidence that the DDSS system is effective in identifying and locating volcanic LPs and tremor. The fiber optic cable is permanently deployed allowing for continuous recording of seismic signals, even during eruptions and thunderstorms, at the station at the foot of the volcano.

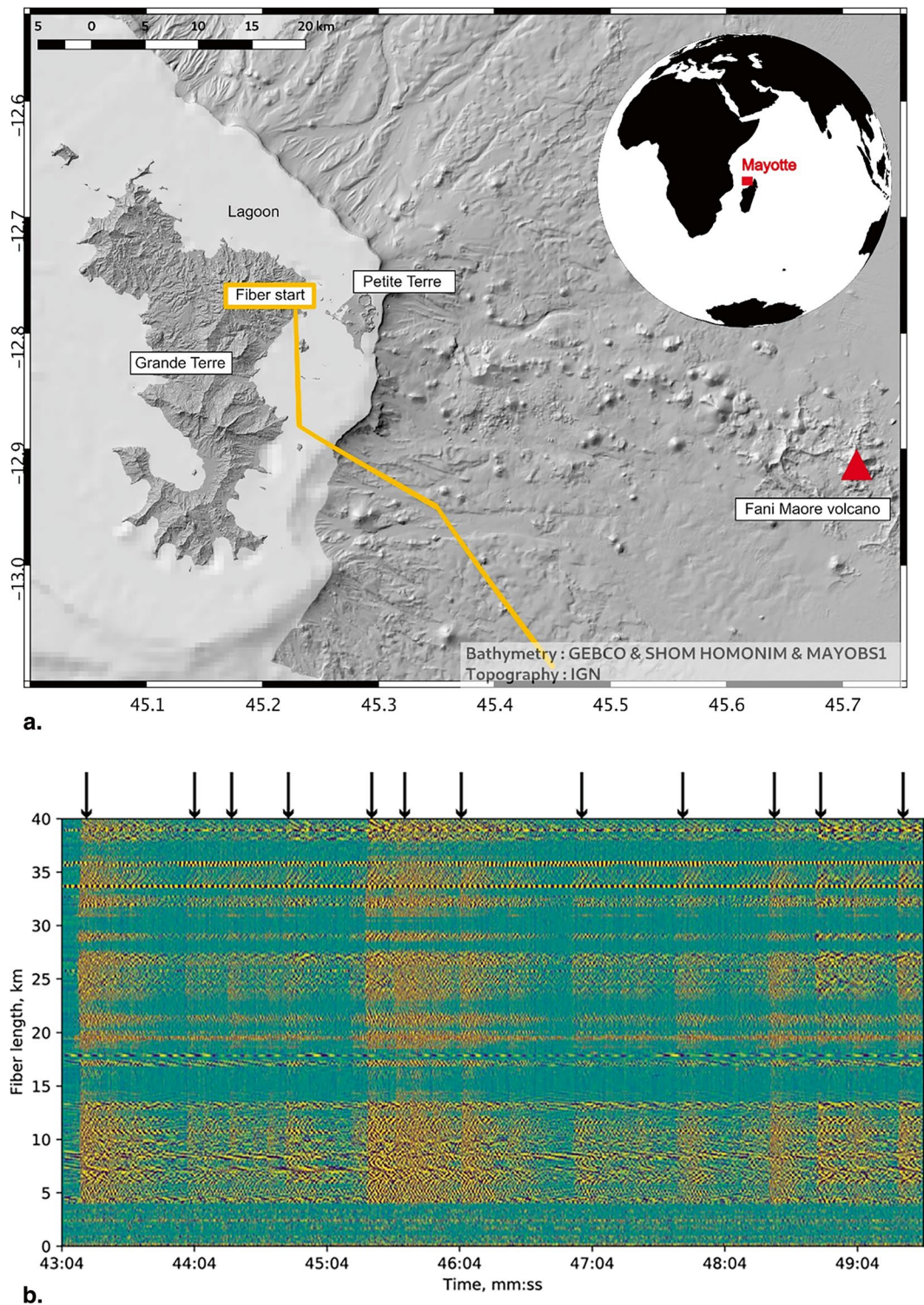


Fig. 5 **a** Map of Mayotte and the fiber optic cable in orange. This telecommunication cable interlinked Comoros main island to Mayotte. The volcano is represented by the red triangles. **b** LP swarm recorded on the 11th October 2020 at 23:43 UTC. Vertical arrows identify the occurrence times of single LP events during the swarm

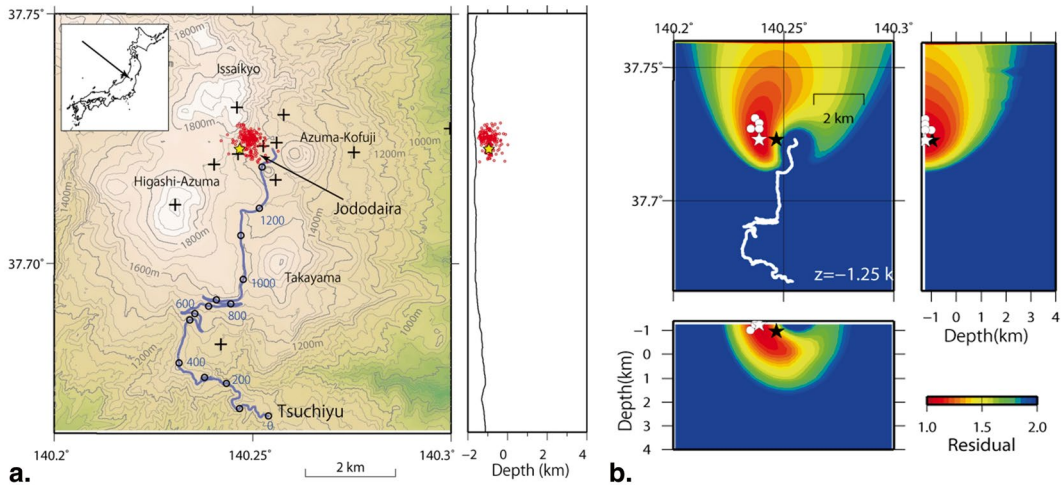


Fig. 6 (Adapted from Nishimura et al. 2021). **a** Locations of the fiber optic cable; the DDSS system is located in Tsuchiyu station, at the south end of the fiber optic cable. The fiber optic cable is indicated by the purple line, and the open black circles denote the locations of the measurement points every 200 channels. “Plus” symbols indicate permanent stations maintained by Tohoku University and the Japan Meteorological Agency. Hypocenters of volcanic earthquakes determined by routine analyses of permanent station data for the period from January 1 to July 4, 2019 are indicated by red circles. In particular, the hypocenter of a volcanic earthquake on July 4 is indicated by the yellow

star. This figure was created by Generic Mapping Tools (GMT) v4.5.5. **b** Source locations of six long-period events (LPs). The white star represents the July 4, 2019 LP source location estimated from the DDSS data combining both travel time and amplitude location methods. White circles indicate locations of five other LP source. The black star indicates the hypocenter (LP event on July 4) obtained by routine hypocenter determination using P- and S-wave arrival times. White lines indicate the location obtained from the fiber optic cable. Color contours represent the residuals between the observed and theoretical values of the arrival time differences and amplitudes for the LP on July 4, 2019

DFOS on ice-covered volcanoes (Mt Meager, Canada and Mt Grímsvötn, Iceland)

Ice-covered volcanoes hide themselves from direct observation, thereby limiting the level of preparedness and possibilities for early warning. Their hazardous features are often related to the rapid melting of ice in the event of an eruption, and they include phreatomagmatic explosions, lahars and sub-glacial floods. This highlights the need for spatially dense monitoring at ice-covered volcanoes, even though the lack of pre-existing fiber-optic networks complicates the data acquisition in the often remote and extreme environments. New fibers have to be deployed and coupled with ice and snow, which potentially moves, melts, or accumulates rapidly, which may limit the longevity of the cables. This section provides a brief summary of fiber

optic sensing experiments on two ice-covered volcanoes, Mt. Meager, Canada (Klaasen et al. 2021) and Grímsvötn, Iceland (Fichtner et al. 2022; Klaasen et al. 2022). The focus here is on logistical challenges and the detection of previously undetected volcano-seismicity.

Mt. Meager is an active volcano in the Garibaldi Volcanic Belt in British Columbia, Canada. Much of its scientific relevance derives from the potential for both geothermal energy exploitation and large landslides, which are expected to become more frequent in response to the rapid melting of its glacier. A major challenge for fiber optic sensing on Mt. Meager was the construction of an autonomous and reliable electrical power source. It consisted of a 5.5 kW generator that charged a 550 Ah battery pack. Nearly 450 l of fuel in a separate tank enabled the experiment to run for 4 weeks. A cable of

3 km length was deployed on the ridge of Mt. Meager and the upper part of its glacier, above 2000 m altitude. Trenching on the volcanic deposits along the ridge was done by hand. On the glacier, a chain saw was used to produce a trench of around 30 cm depth. All of the equipment was transported by helicopter.

The installation in autumn 2019 was followed within a few days by the first snowfall of the winter, which visibly improved cable coupling and signal-to-noise ratio. This enabled the unexpected detection of around 3000 seismic events at frequencies between 5–45 Hz, thereby demonstrating that Mt. Meager is considerably more active than previously thought. Beamforming locates most of these events within five major clusters possibly beneath the main peak and in the nearby Lillooet Valley, suggesting a geothermal origin. At lower frequencies, between 0.01–1 Hz, the fiber optic data reveal the presence of volcanic tremor periods that tend to last for several hours and have not been observed before. Both the high- and low-frequency seismicity may become a valuable component in the monitoring of future geothermal energy projects.

While the last eruptive period of Mt. Meager dates back nearly 2500 years, Grímsvötn produces major eruptions on a decadal time scale and is one of the most productive volcanic systems on Earth. Covered entirely by Europe's largest glacier, Vatnajökull, its caldera with 10 km diameter hosts a subglacial lake that regularly produces outburst floods and inundations of the coastal plains. During springtime, the research huts located on the highest point of the caldera can be reached with skidoos, meaning that the transportation of equipment does not require expensive helicopter flights. The installation of a 12.5-km-long fiber optic cable around and inside the caldera was achieved within 3 days thanks to the construction of a custom-built trenching sled, equipped with a ca. 50 cm deep plough that placed the cable directly into the ice. Electricity and an internet connection were available in one of the huts, thereby permitting continuous recording for 3 weeks, as well as online trouble-shooting and optimization of the interrogator setup.

The excellent shielding from wind and temperature variations enabled the recording of a wide range of seismic signals, sometimes with amplitudes below 10 nanostrain/s. During the experiment, nearly 2000 local events could be detected using an image processing algorithm adapted to distributed fiber optic sensing (Thrustarson et al. 2021). Most of these events occurred within few clusters between 1 and 3 km depth beneath the western part of the caldera. Possibly owing to their low magnitudes, roughly between -2 and 0.5 , the majority of these local earthquakes have not been detected by the regional seismometer network, which attests to the importance of fiber optic sensing in high-resolution volcano monitoring.

A more exotic observation at Grímsvötn is the nearly monochromatic oscillation of its caldera at 0.22 Hz, which corresponds to the fundamental-mode resonance frequency of the ice sheet that floats atop the subglacial lake (Fig. 7). The time dependence of the oscillation amplitude does not correlate with the amplitude of the ocean wave-generated ambient field, suggesting that the resonance is driven by a local process. In the absence of other plausible explanations, the ice sheet apparently acts as a natural amplifier of nearly continuous volcanic tremor that would otherwise not be observable (Fichtner et al. 2022).

Earthquake detection and location with a rotational sensor (Etna Volcano, Italy)

Eibl et al. (2022) conducted a performance test on the blueSeis-3A rotational sensor, which was co-located with a broadband seismometer. The blueSeis-3A sensor has a height of 30 cm, a diameter of 30 cm and weighs approximately 20 kg (Fig. 1). It consists of three fiber loops arranged in three orthogonal axes that measure the rotation rate in nanoradian/second (Bernauer et al. 2018). The sensor has a flat instrument response from 0.001 to 50 Hz and the ground motion is typically digitized and recorded at 200 Hz. To protect the instrument from wind noise, it should be buried. Currently, the instrument has a power consumption of

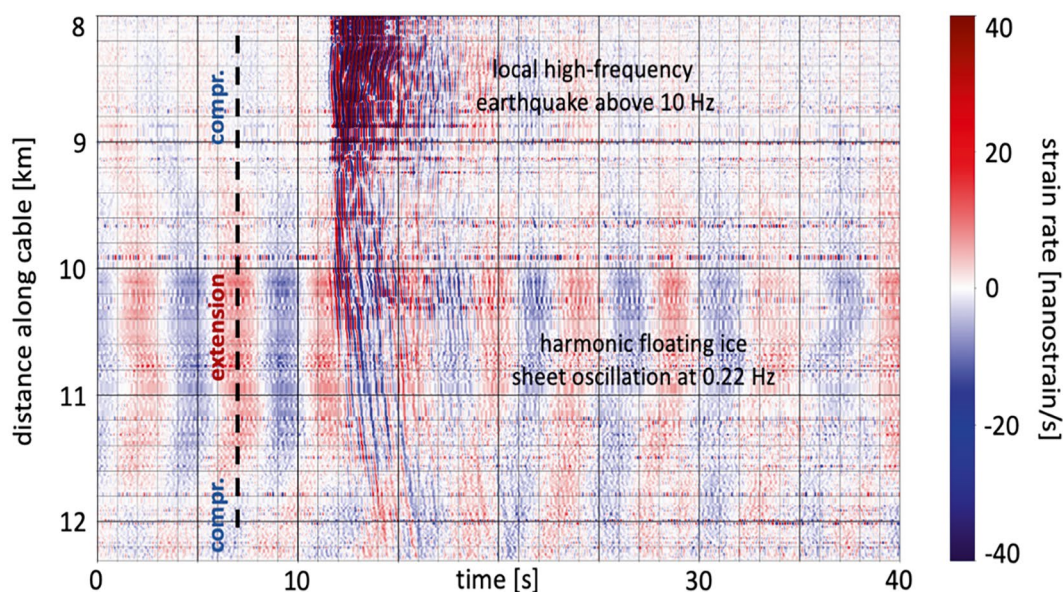


Fig. 7 (Adapted from Fichtner et al. 2022). DDSS record section of 40 s length from within the caldera of Grímsvötn. The signal from a high-frequency local earthquake is superimposed onto the nearly monochromatic

oscillations of the ice sheet that is floating atop the subglacial lake. The dashed black line marks at this chosen time where one can observe extension in one and compression (“compr.”) in another part of the caldera

21 W. Although the portable rotational sensor blueSeis-3A is less sensitive than a conventional seismometer, it can still measure weak volcano-seismic signals if the distance between the source and the sensor is less than a few kilometers. The use of a rotational sensor (3C, rotational components) in combination with a seismometer (3C translational components) defines a “6C station”. This type of combined station is best suited for computing back-azimuth and locating seismic events.

Eibl et al. (2022) deployed a 6C station at approximately 2 km from the five active craters of Etna volcano (See Fig. 4, station bb17) to test its ability to detect and locate volcano-tectonic (VT) events, long-period (LP) events and tremor. The validation was performed by comparing the locations of volcanic earthquake locations recorded by the 6C station with the locations from the permanent monitoring network of the Istituto Nazionale di Geofisica e Vulcanologia - Osservatorio Etneo (INGV-OE). During a one-month of acquisition period in August and September 2019, Eibl et al. (2022)

compared the number of detections obtained by each instrument separately with the number of events detected by the permanent seismic network. The number of VT events detected using either only the rotational sensor or only the seismometer is similar. However, in both cases, this number is slightly less than the number of events detected by the INGV-OE network. The seismometer detected a comparable number of LP events compared to the INGV-OE network on most of the days, and three times more LP events than the rotational sensor. The rotational sensor revealed the SH-type wave nature of the LP events, as they were only detected on the vertical component of the rotational sensor (Fig. 8). Similarly, during weak strombolian activity, the tremor wave field is dominated by SH-type waves. However, during sustained strombolian activity, the wave-field changes to a mixed-type. The back azimuth of the derived tremor is consistent with the INGV-OE estimates, and the derived phase velocities derived by (Eibl et al. 2022) are consistent with the velocities derived using DDSS records (Jousset et al. 2022).

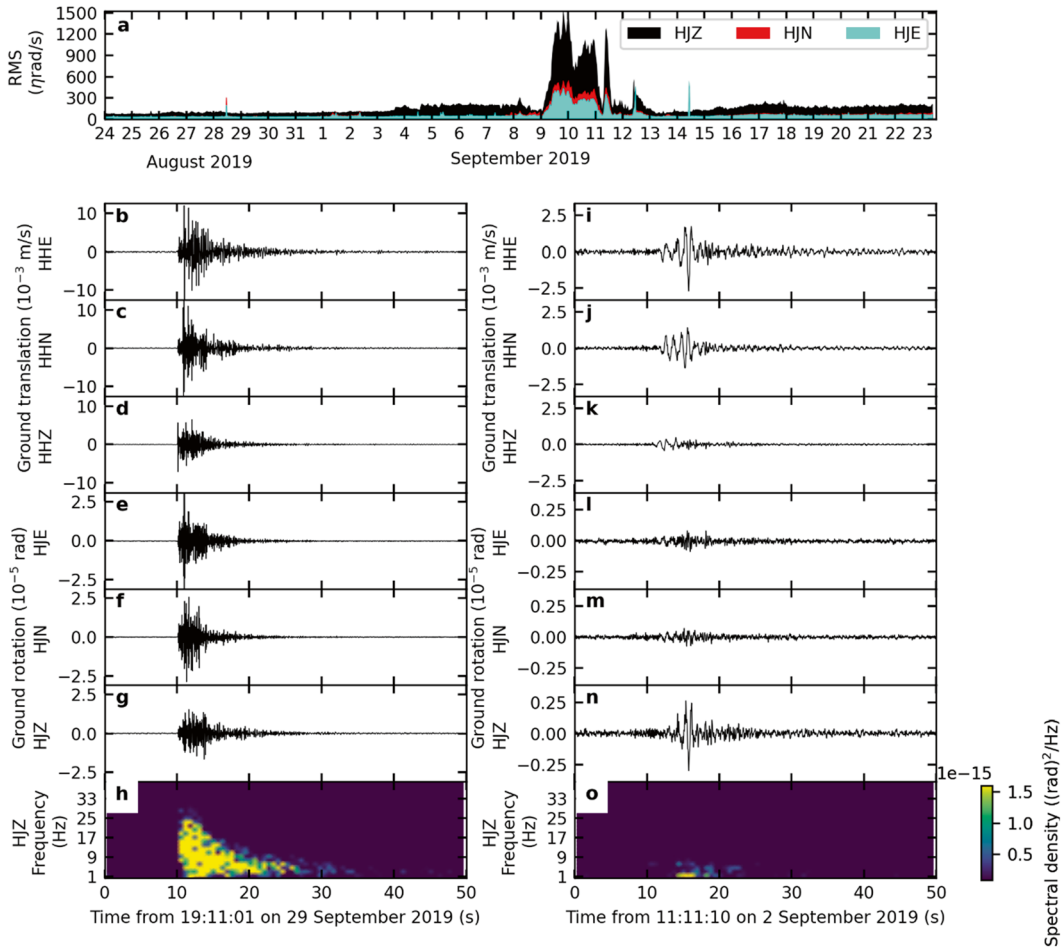


Fig. 8 (Adapted from Eibl et al. 2022). VT, LP and tremor events were recorded with conventional seismometer and rotational sensor at Etna volcano, Italy (Eibl et al. 2022). The transition from a SH-wave dominated to a mixed wave field occurred in the period 9 to 13 September 2019. **a** Amplitude of the rotational sensor signal for one month of record. **b–h** Records for a

volcano-tectonic (VT) event recorded on 29.09.2019. **b–d** Conventional seismometer and **e–g** rotational sensor. **h** Spectrogram (HJZ component). **i–o** Records for a long-period (LP) event recorded on 2 September 2019. **i–k** Conventional seismometer and **l–n** rotational sensor. **o** Spectrogram (HJZ component)

3.3 Structural Features of Volcanic Media

Understanding the structure of a volcano is crucial for comprehending its internal dynamic processes. For instance, the locations of volcanic hypocenters (Koulakov and Shapiro 2021) or source mechanism (Bean et al. 2008) may be entirely inaccurate, if an unsuitable velocity or structural model is employed.

DFOS has been demonstrated to be a valuable tool for near-surface characterization (Ajo-Franklin et al. 2019) particularly in urban areas where performing conventional active seismic surveys is challenging. The dense network of dark fibers in cities enables the investigation of shallow subsurface properties using techniques such as ambient and anthropogenic noise, such as cars (Jousset et al. 2018). In this section, we show that DFOS can be valuable for conducting

thorough structural analyses of volcanic materials.

Fault detection (Reykjanes, Iceland)

A clear example of the impact of DFOS on discovering structural features associated with faults in volcanic environments was demonstrated in the South-West of Iceland (Jousset et al. 2018). The objective was to show that fiber cables already deployed for telecommunications could be interrogated with Distributed Dynamic Strain Sensing in a useful manner for volcano-seismology. The goal was achieved by recording of a local earthquake (M 1.1) that occurred beneath the cable. The cable used in this study

was buried 80–90 cm below the ground surface crossing the Svartsengi geothermal field from the southern tip of Reykjanes to Grindavík. Figure 9 shows the response of a local fault zone that is partially visible at the surface, with a clear indication of the diverging plate tectonic processes. When seismic waves propagate, their energy tends to remain in areas where the seismic impedance is lower (Jousset et al. 2003). The dense spatial sampling (one time series every 4 m) allows for clear observations of trapped waves inside the fault zone. Scattering of waves can be observed, opening up possibilities for studying the physical properties of materials inside fault zones (Atterholt et al. 2022; Yang et al. 2022).

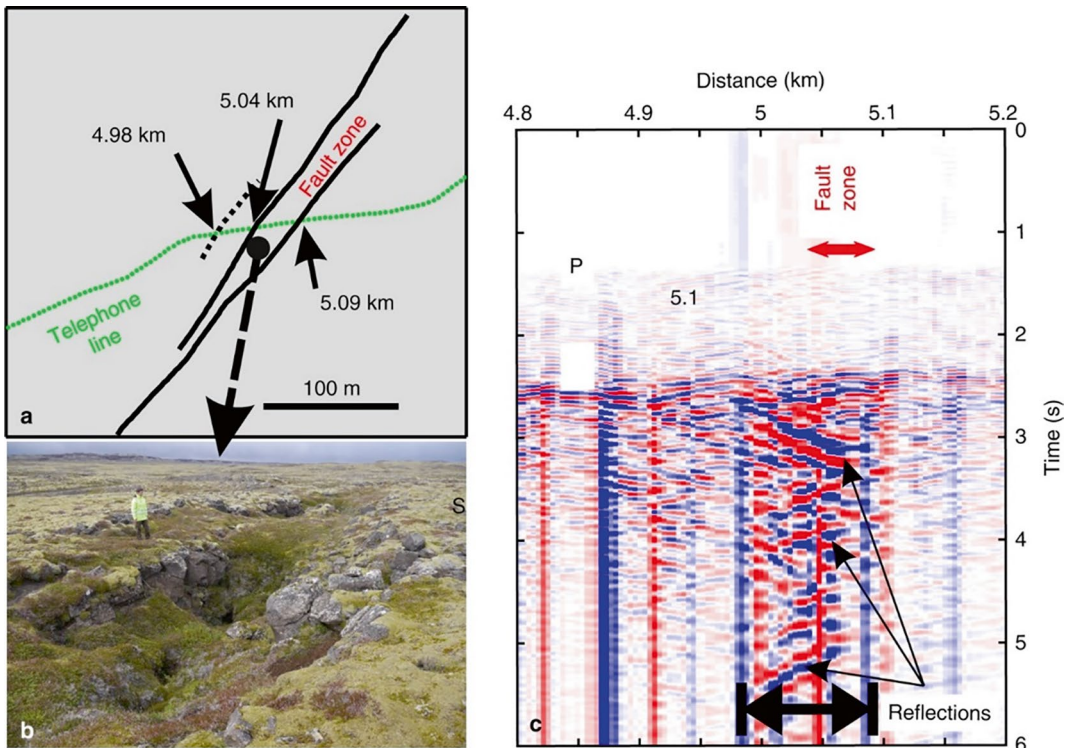


Fig. 9 (Adapted from Jousset et al. 2018). Structure of a fault damage zone within an active geological rift. **a** The road and the cable (distance ~5 km) cross several faults, e.g. a clearly visible fault zone with more loose material in the field (between 5.04 and 5.09 km). **b** The fault damage zone is visible by the ~50–60 m wide depression area (picture taken at ~100 m SW of the road, looking towards SW). Note that at the cable location no

depression area is visible. The depression is only the surface expression at the position of the picture (Picture Martin Lipus, GFZ). **c** Short record (6 s) of strain phases from a local earthquake trapped in the fault damage zone. Phases are reflected until ~4.98 km, which may indicate a hidden fault with surface expression. Waves inside and outside the fault zone have different apparent velocities

Material characterization of volcano subsurface (Mt. Azuma, Japan and Etna volcano, Italy)

To comprehend the underlying volcanic source mechanisms, it is crucial to characterize the subsurface at volcanoes (Bean et al. 2008). DFOS can be particularly useful, especially when the optical cable is already installed. Nishimura et al. (2021) highlight that DFOS records can be used to determine site amplification factors and relative amplitudes of coda waves of regional earthquakes at Azuma volcano. The data show a

strong correlation between the fiber optic cable and subsurface volcano structures, including lava flows and topography (Fig. 10). However, as the fiber optic cable is deployed in a protecting plastic tube by a telecom company, its coupling with the ground is not well understood.

If the fiber optic cable is not already in place, a dedicated cable can be deployed. For instance, Jousset et al. (2022) deployed a dedicated cable directly into a scoria layer at Etna volcano (Figs. 1 and 11), resulting in optimal and consistent coupling with the ground along the entire cable. Advanced and powerful methods

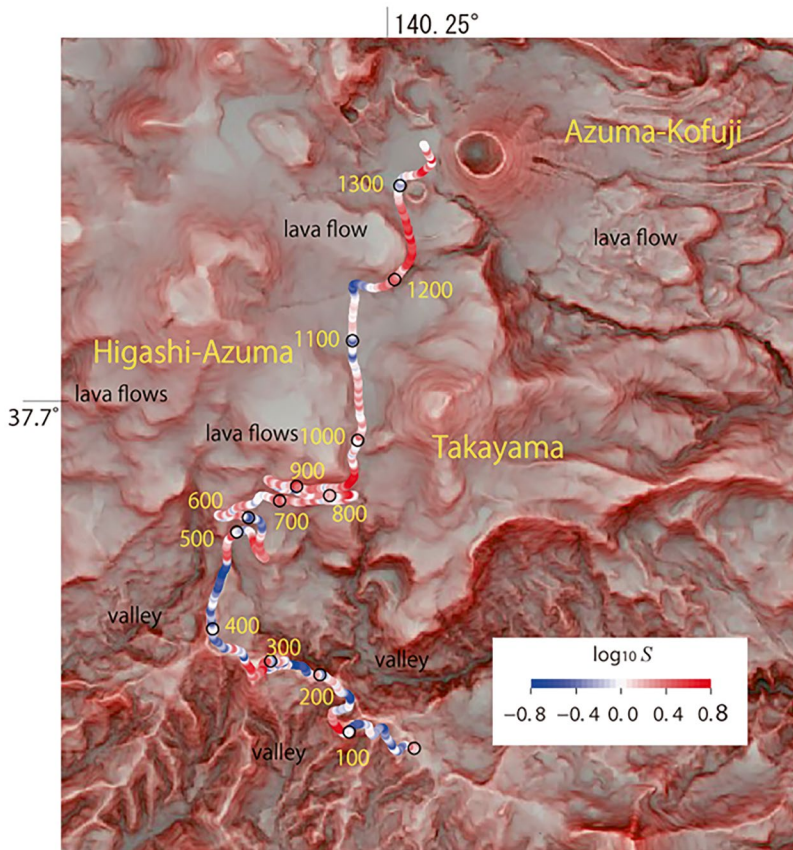


Fig. 10 (Adapted from Nishimura et al. 2021). Site amplification factors along the fiber optic cable. Logarithmic amplitudes of the factors are indicated by color contours. Background is a red relief map emphasizing topography of the volcano provided by the Geospatial Information Authority of Japan. Numbers along the cable

are trace numbers. Large site amplification factors, S , are recognized around the lobes of old lava flows extending from the active volcanoes (traces around 500–1050 and 1200–1300), while small site amplification factors are mainly found on the ridges around steep valleys in the southern part (traces around 350–450, 200 and 1–100)

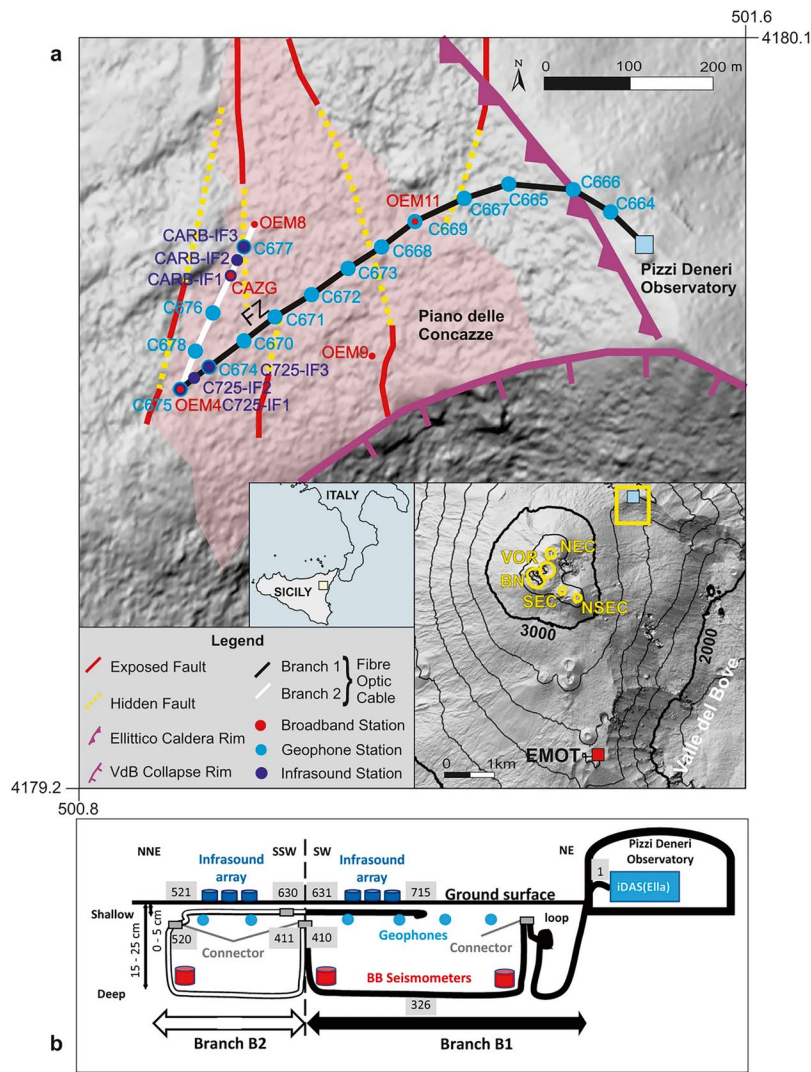


Fig. 11 (Adapted from Jousset et al. 2022). Fiber optic cable, seismometer and infrasound sensor locations and deployment near Etna volcano summit (Piano delle Concazze) and Valle del Bove on the digital elevation model. **a** The iDAS interrogator set up at Pizzi Deneri Observatory (light blue square), is connected to the fiber indicated by the black (“branch B1”) and the white (“branch B2”) lines, respectively. **b** Sketch of the cable deployment. From the interrogator (inside and around the observatory, channel 1–50), the cable is buried in compacted material (channels 50 until 200) and then in loose scoria deposits (transparent reddish area in **a**), at about 15–25 cm depth (deep section) along B1 with channels 1 to 410, then the cable turns (still within the deep

section) along B2 with channels 411 until 520, then the cable has a shallow section (under a few cm of scoria and lying directly above the deep cable), from channels 521 until 630 (with same geographic location as deep channels 520 until 411, respectively), and finally, the shallow cable turns along B1 (still above the deep cable) from channels 631 until 715 (with same geographic location as deep channels 410 until 326). Insets: Local and regional contexts. Summit craters’ locations: NSEC (New South-East Crater); SEC (South East Crater); BN (Bocca Nuova); VOR (Voragine); NEC (North-East Crater). Red square: Thermal camera location: EMOT. The yellow box indicates the location of the main map. This figure serves as map for Figs. 12 and 13 of the chapter

of subsurface structural exploration could be performed, such as Multi-channel Analysis of Surface Waves (MASW; Park 2011; Lancelle et al. 2021). MASW provides dispersion curves that can be inverted to obtain vertical 1D shear wave velocity profiles. Jousset et al. (2022) performed jumps also known as tap tests, at various locations along the cable to geo-locate the distributed sensing records. The jumps can also serve as sources of surface waves for MASW analysis. For each jump performed along the cable, two sub-datasets were obtained: a forward sub-dataset (records towards increasing channel numbers) and a backward sub-dataset (records towards decreasing channel numbers). The dispersion curve was computed using the phase-shift method (Park 2011). It is worth noting that the seismic wave field separation method (Schwarz 2019) was used to improve the signal to-noise ratio of the dispersion curves. Finally, the observed modes in the dispersion curves were picked. Using a Markov chain Monte Carlo scheme (Killingbeck et al. 2018) the picks were inverted to derive a vertical profile of shear wave velocities for both the forward and the backward subsets. Figure 12 demonstrates two examples of this procedure, showing that subsurface structures can be determined using MASW on fiber optic dynamic strain data sets. The dispersion analyses show numerous modes, indicating a strongly dispersive medium due to multiple superposed volcanic strata with varying velocities. This is consistent with a sequence of lava flows and scoria deposits. Inversions of these dispersion curves yield vertical profiles of layers. The first layer with shear-wave velocity of 200 ms^{-1} and 3–5 m thickness. Deeper layers have velocities up to 600 ms^{-1} at about 20–25 m depth. The inverted models reflect structures associated to faults and lava flows at the volcano (Napoli et al. 2021).

3.4 Dynamics of Volcanoes: Monitoring Degassing with Fiber Optic Cables

Gas is one of the fundamental drivers of volcanic activity, with two end-members: passive degassing occurs gently through structural features of the volcano (Segovia 1991), while explosive degassing occurs when the strength of the structural feature is exceeded, e.g., due to high gas flux. Therefore, it is essential to monitor degassing and study the underlying driving processes. This section reports examples of two end-members using DFOS: a volcanic explosion at Etna volcano (Italy) and degassing through bubbles in a volcanic lake, the Laacher see (Germany).

Volcanic explosions (Etna volcano, Italy)

Volcanic explosions happen when the strength of the rock cannot withstand the overpressure caused by magmatic and/or hydrothermal fluids. This can occur when there is lower rock permeability within the volcanic conduit, which prevents higher fluid flux and causes overpressure. To study explosive events, infrasound and seismic signals can be used (Johnson and Ripepe 2011). In the summer of 2018, Jousset et al. (2022) deployed a temporary array of multiparametric sensors at Etna volcano. The array consisted of a 1.3 km standard fiber optic cable buried in a trench of approximately 20 cm deep into a scoria layer. Additionally, a series of geophone and infrasound sensors were deployed along the cable (Fig. 11). The sensors recorded volcanic explosions (Fig. 13). These volcanic events produce seismic waves which travel in the ground faster than the acoustic waves in the atmosphere. The volcanic material exhibits a non-linear response when the infrasound wave

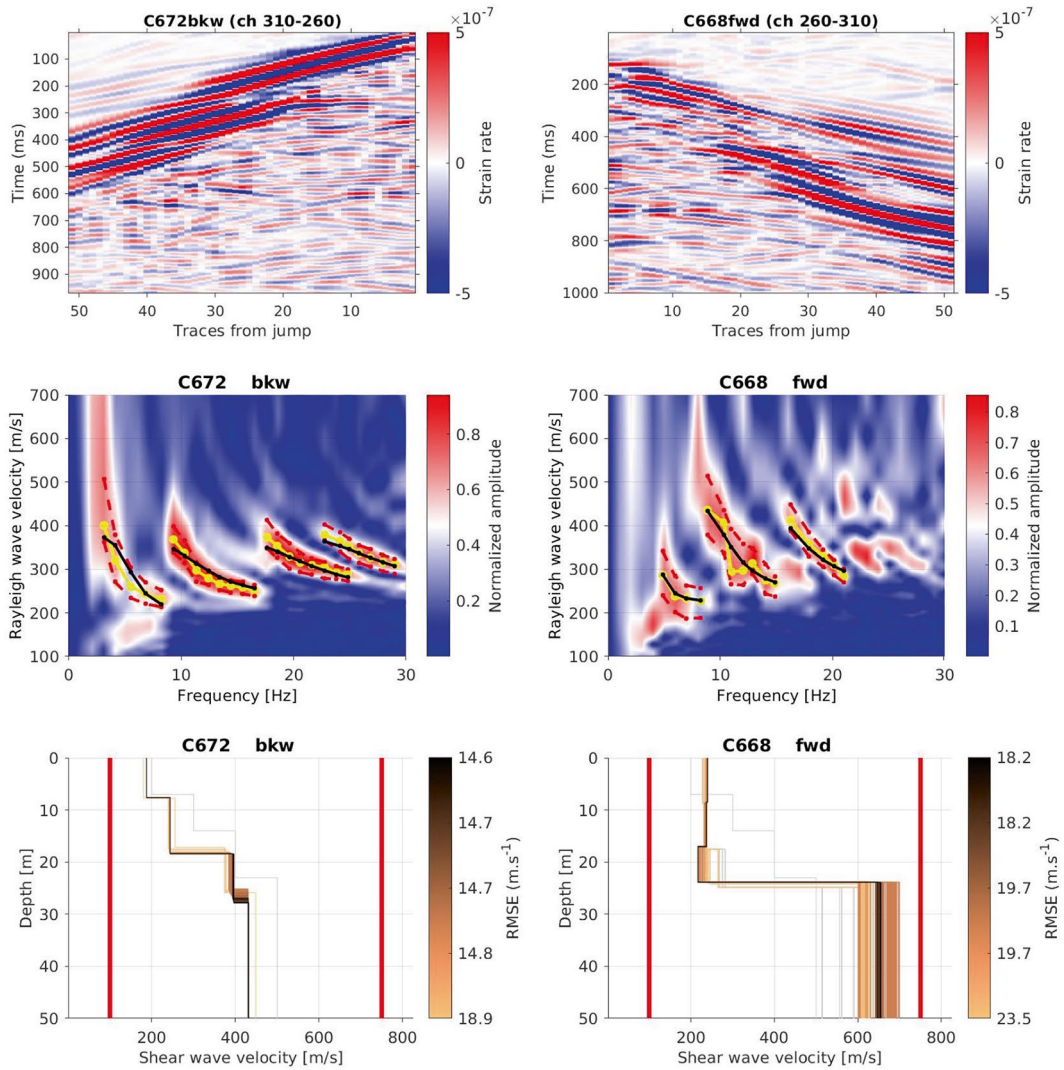


Fig. 12 (Adapted from Jousset et al. 2022). Multichannel Analysis of Surface Waves (MASW) and Markov chain Monte Carlo inversion of dispersion curves from DDSS records along a cable of 1.5 km at Etna volcano along the cable shown in Fig. 11. Graphs represent analysis results for 2 jumps performed at locations given by the name of co-located geophones (C668, left column and C672, right column). Jousset et al. (2022) define a forward branch (fwd) signals for channel numbers larger than the channel of the jump, and a backward branch (bkw) signals for channel numbers smaller than the channel of the jump. The fwd and bk records are both used separately for the dispersion curve analysis. **(Top subplots)** Enhanced strain signals

(Method: Coherent wave field enhancement and separation). **(Middle subplots)** Dispersion spectra in phase velocity/frequency domain. Green dotted lines are the picked dispersion values with their corresponding uncertainty (red dotted lines). Black dotted lines represent the multimode dispersion curves computed using the best inverted model causing the lowest root mean square error (RMSE). **(Bottom subplots)** 1D wave velocity retrieved after Markov chain Monte Carlo inversion. Red lines indicate limits of tested models during the inversion. In contrast to the backward branch at C672, the forward branch at C668 crosses a major structure in the form of a fault zone causing a more complicated Rayleigh wave field (Fig. 11)

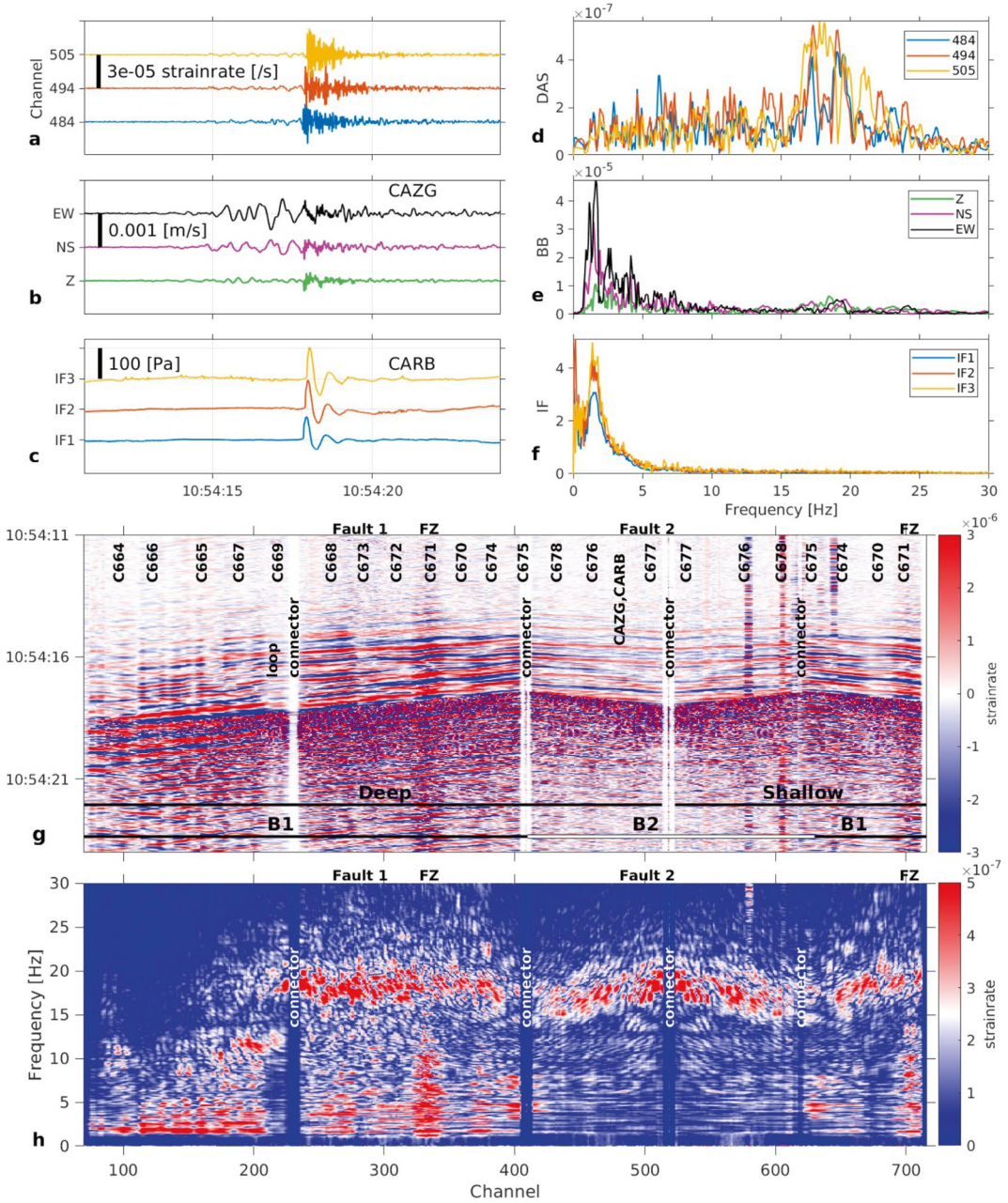


Fig. 13 (Adapted from Jousset et al. 2022). **a** Strain rate from distributed dynamic strain sensing (DDSS) records at channels 484 (blue), 494 (red) and 505 (yellow), corresponding to positions of infrasound sensors in **c**. Fiber channel position accuracy ± 3 m. **b** Velocity seismograms from broadband seismometer CAZG, near DDSS channel 494. **c** Pressure records from infrasound sensors CARB-IF1, 2, 3. **d** Strain rate (**a**) spectra. **e** Ground velocity (**b**) spectra. **f** Pressure (**c**) spectra. **g** Strain rate record at the 710 DDSS channels along the 1.3 km fiber

around the explosion time. B1 and B2 are two geographically distinct branches, oriented in two different directions. FZ: fault zone (~ 50 m width), at channels 315–340 (deep cable) and channels >700 (shallow cable). **h** Strain rate-frequency distribution along the cable. Note higher strain rate amplitudes at low frequencies 1–10 Hz (seismic signal) for branch B1 and at high frequencies 18–21 Hz (infrasound induced signal) for both branches (see Fig. 11 for locations)

encounters the scoria layer in which the cable is buried. This is indicated by the presence of a high-frequency signal (18–23 Hz), that is absent in the infrasound signal.

Bubbles and degassing (Laacher See, Germany)

Passive gas monitoring is typically carried out by directly sampling fumaroles in the crater (Chiodini et al. 2011) or through remote sensing (Taddeucci et al. 2021). The relationship between seismic activity and gas flux has also been identified and studied (Zuccarello et al. 2013). During a period of quiescence (no eruption) at Etna volcano, Jousset et al. (2022) used DFOS to identify STP (Small Tremor Pulse) and DG (degassing) signals as slightly larger amplitude phases within the volcanic tremor. These signals were interpreted as resulting from variations in the uprising gas flux within the volcanic conduit until the vent. Degassing processes at quiescent volcanoes can help detect potential signs of unrest, as shown by Caudron et al. (2024) at the volcanic lake Laacher See (Germany). The lake is situated in a caldera, indicating past violent volcanic activity within a large volcanic complex in the Rhine graben. In recent years, there has been signs of possible unrest, identified by the occurrence of

deep LP earthquakes and possibly large-scale deformation (Hensch et al. 2019). During June–July 2021, an experiment was conducted to test DDSS by deploying a 500 m long fiber optic cable on south-western side of the lake at a depth of approximately 20 m (Fig. 14a). The coupling at the bottom of the lake was ensured by two divers. Strain rate measurements were collected at a spatial resolution of 1 m and different temporal sampling rates (5 and 8 kHz). Videos of the dynamic of underwater bubbles were simultaneously acquired with a smartphone, enabling observations of bubbles rising from the sediment towards the surface at different times. The experiment recorded occurrence rates and frequencies. Close to the bubbling spots, the waveforms are similar to the signals recorded by Vasquez et al. (2015) during laboratory experiments. The signal observed in the lake had a high-frequency onset of approximately 1 kHz, followed by a lower frequency signal at around 200 Hz (Fig. 14b). The signal waveform varied slightly along the cable with decreasing signal-to-noise ratio, as a function of distance from the main bubbling spot. However, it is also possible that changes may be related to different coupling conditions. These results suggest that DDSS technology is sensitive to degassing under water, and therefore could be used for monitoring submarine bubble flux.

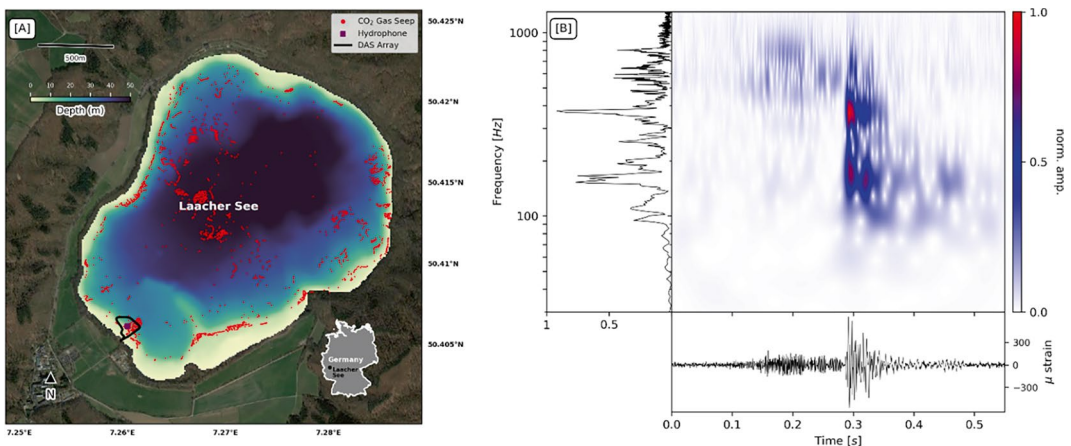


Fig. 14 **a** Laacher See aerial image and location of the fiber optic cable (triangle in red to the South). **b** Spectrum (left), waveform (bottom) and spectrogram (center) associated with a bubbling event

3.5 Monitoring Long Term Deformation (Etna Volcano, Italy)

BOTDR can be used to measure “quasi-static” deformation. A BOTDR interrogator (Fig. 1) was attached to a submarine cable in the port of Catania, Italy. The results show increasing strain along the cable for the first 5 km of the cable from May to September 2020 followed by a sustained drop in strain thereafter (Fig. 15). This variation occurred during a period of significant inflation and deflation before and after the paroxysmal episodes in December 2020 and January 2021. Terrestrial GNSS stations have observed the phenomenon on land (Bruno et al. 2022). This preliminary result demonstrates the potential of BOTDR in locating zones of deformation at high resolution and sensitivity in submarine environments surrounding volcanic islands, where obtaining measurements is challenging. As Brillouin scattering is influenced by temperature (see Sect. 2.3.2), temperature fluctuations must be accounted for when measuring

strain near the surface. However, for submarine cables, temperature variation is lower than on the ground surface. Ongoing research aims to invert for both temperature and strain simultaneously (Bao et al. 2021).

4 Towards Integrating Fiber Optic Technologies Within Volcano Monitoring Systems

Volcano monitoring involves continuously observing key parameters and their variations on an active volcano in order to estimate its activity status, anticipate its behavior before an eruption, forecast the probability of an eruption and define potential scenarios to improve risk management (e.g., Thierry et al. 2015). To achieve this goal, it is necessary to locate earthquakes, identify fluid movements within the volcano, and understand the sources of slow inflation/deformation, in real-time. Section 3 illustrated that the full wave field can be measured, providing examples of promising approaches that could improve the

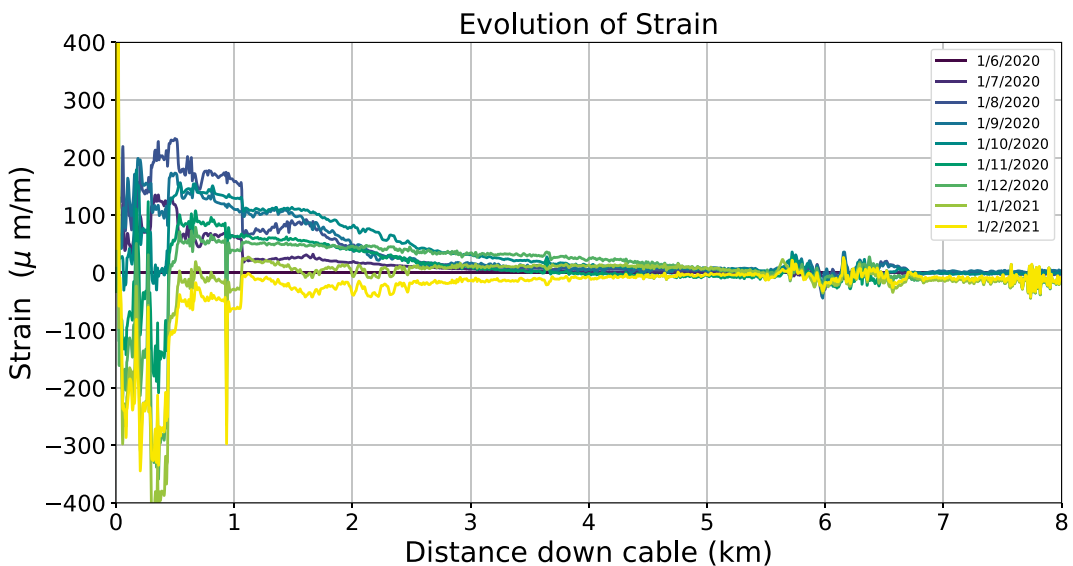


Fig. 15 Strain variation along fiber optic cable deployed offshore Catania using a BOTDR interrogator. X-axis is the distance down the cable with measurements taken every 4 m and averaged over the whole day. The strain

measurements have been taken over the course of a day at the start of each month and averaged. All strain measurements are set relative to 1 June 2020 (dark blue line). Line color denotes time that strain measurement was taken

monitoring capabilities of volcano observatories. This section illustrates and discusses how fiber optic methodologies could contribute to operative volcano monitoring.

4.1 Integration of DFOS in Existing Monitoring Systems

Monitoring seismicity: combination of seismometers and DDSS measurements (Reykjanes, Iceland)

The combination of fiber optic Distributed Dynamic Strain Sensing data via fiber optics and conventional seismometers can be an effective approach for accurately locating seismic events. For instance, Flovenz et al. (2022) showed that the combination of data from a fiber optic telecom cable with data from 26 broadband seismic stations enhanced the detection of earthquakes and improved their location accuracy during the swarm of volcano-tectonic earthquakes before the Geldingadalir eruption 2021 (the first eruption of the Fragaradalsfjall fires, Halldórsson et al. 2022). By using a waveform stacking and migration method, seismic and continuous DDSS data were combined to produce a complete earthquake catalogue covering the period from 1 February 2020 to 30 August 2020. A total of over 39,500 VT earthquakes occurring in swarms with magnitudes of $M > -1$, were automatically detected and located. The seismic sensors and the optical cable were located directly above the hypocenters, ensuing a good azimuthal distribution of all stations, resulting in high quality lateral and vertical hypocenters. Seismicity shallower than 4 km depth was concentrated within an elliptical area, where an uplift occurred. The uplift was interpreted as resulting from the vaporization of water from an aquifer, which is being harnessed by a geothermal company. The study of Flovenz et al. (2022) suggest that the earthquakes at the center of the uplift are triggered by elastic bending stresses in the roof above the aquifer. The absence of earthquakes deeper than 4 km depth at the uplift

center supports the hypothesis of an up-doming brittle ductile transition (BDT) at about 6–7 km depth (Fig. 16 and Flovenz et al. 2022).

Multi interrogator approach (Etna volcano, Italy)

Cables are linear objects, and their aperture may not be sufficient to cover the ideal network for optimal hypocenter location (Toledo et al. 2020). To increase the aperture and the spatial coverage for larger targets, such as Etna volcano, multiple fibers and interrogators can be used simultaneously. The availability of several interrogators at once is a clear issue. At Etna volcano, three independent interrogators were connected with three different fiber optic cables for about ten days from 11 September 2019 to 23 September 2019 (Krawczyk et al. 2020). The INGV permanent monitoring network recorded a total amount of 134 local seismic volcano-tectonic earthquakes. Figure 17 shows the records of an M2.4 earthquake located in Valle del Bove at a depth of 4.3 km with three fiber optic cables at once.

It is worth noting that the amplitudes of the strain rate signals do not follow the expected geometrical amplitude decay of seismic waves from the source to the fibers. This discrepancy may be due to the variety of coupling conditions between the ground and the different cables, as observed at Mt. Azuma (Fig. 10). The cable at the summit was perfectly coupled with scoria (Currenti et al. 2021; Jousset et al. 2022; Figs. 1 and 4). On the contrary, the telecom cable in the urban environment on the Eastern flank is likely to be deployed in pre-existing cased conduits and therefore transfer of ground strain to the fiber core is less efficient (Reinsch et al. 2017). Underwater, the recorded strain may be lower due to the cable's coupling conditions with the sea floor, and its increased strength to withstand water column pressure at a depth of 2000 m and submarine currents. This prevents ground strain from being transferred to the sensing fiber (Currenti et al. 2023; Diaz-Meza et al. 2023).

Nevertheless, the event's location can be determined using basic automatic picking

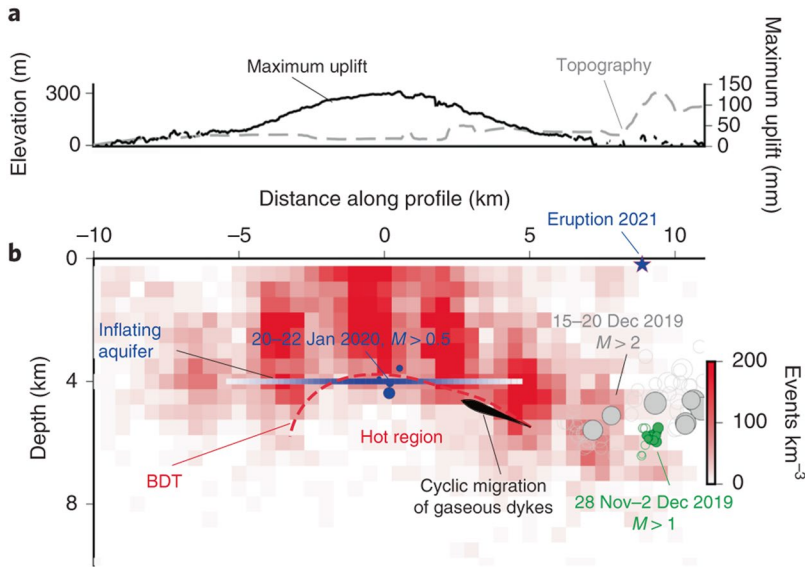


Fig. 16 (Adapted from Flovenz et al. 2022). Sketch of fluid migration paths and aquifer location compared with observed seismicity and uplift. **a** Maximum uplift (solid black line) and topography (dashed grey line, $x=0$ at the center of the uplift). **b** Density of micro-earthquakes between February and August 2020 (gridded file and color scale) estimated in a 1-km-wide band along profile SW-NE using a combination of broadband

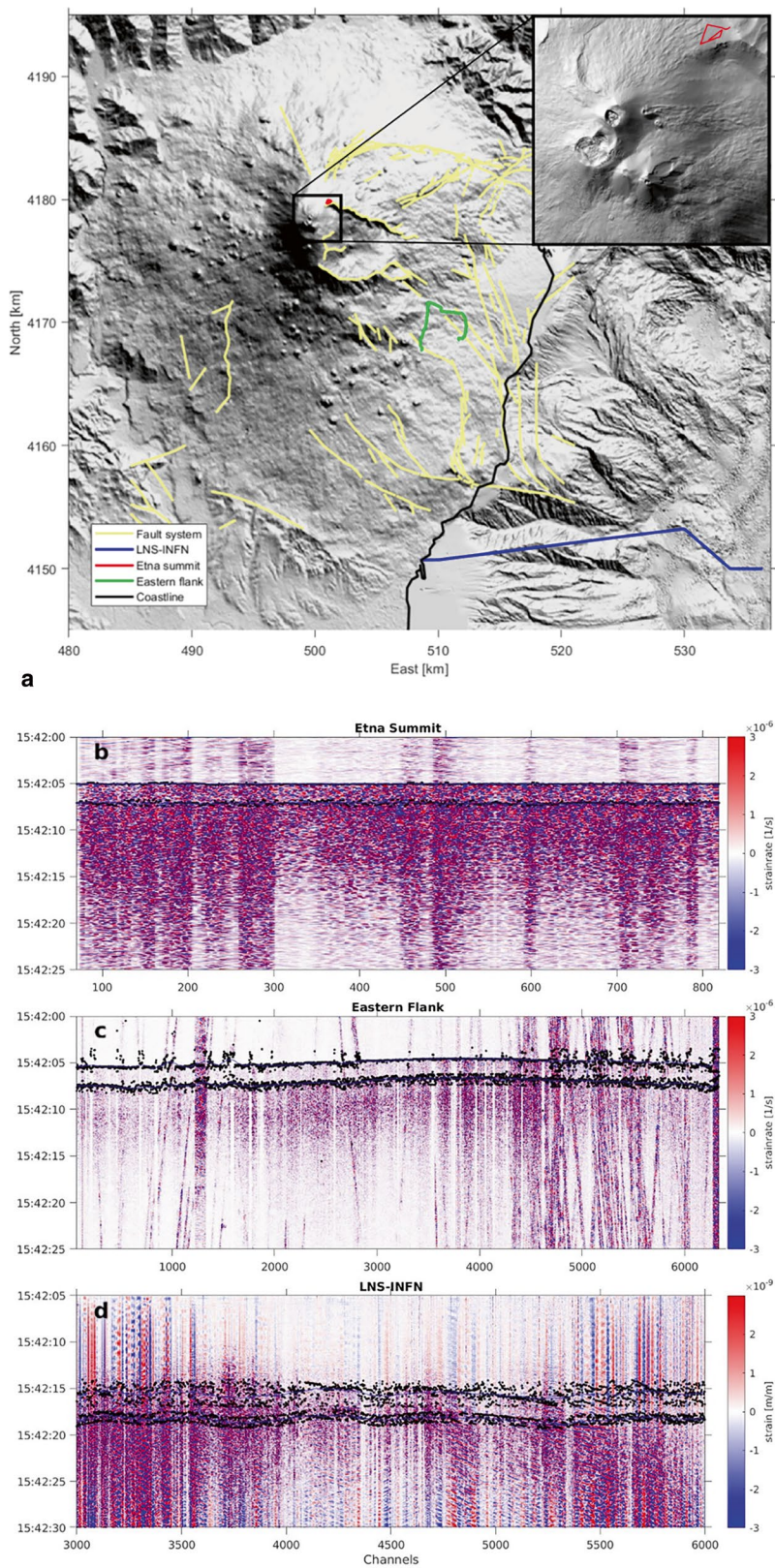
seismic stations and Distributed Dynamic Strain sensing. The inferred brittle ductile transition (BDT) is indicated by the red dashed line. The manually relocated, largest events from the earthquake swarms from November (green circles) and December 2019 (grey circles) and at the beginning of unrest (blue circles) are shown. The position and source intensity of the aquifer model are indicated

(Jousset et al. 2011, 2018) based on arrival times detected on two of the three cables (Fig. 17). The black dots on each fiber represent the automatically picked times for both P- and S-waves arrivals, using a non-cable-specific and unoptimized STA/LTA algorithm. To perform the location inversion, a spatial interpolation is conducted between picks to eliminate the scattering caused by local conditions and to attempt to remove anthropogenic signals. The interpolated picked arrival times are then used to conduct an

inversion for the location using a grid search, resulting in a probability density function of the earthquake’s location. This hypocenter encompasses the INGV location obtained from conventional seismometers in the monitoring network. This example demonstrates that by designing a suitable series of interrogated fibers, either by deploying dedicated cables or/and interrogating already existing ones, distributed dynamic strain methods can provide new and dense information to better locate earthquakes.

Fig. 17 **a** Map of Etna volcano indicating the locations of the three cables interrogated simultaneously. **b–d** Records of a volcano-tectonic earthquake on the 15 September 2019 at 15:42:02 in Valle del Bove with several fiber optic cables. Back dots represent the automatic picking of P and S for each channel, using STA/LTA conventional detector and an Akaike Information Criteria picker (Jousset et al. 2011, 2018). **b** PDN array, at the summit of Etna volcano (spatial sampling 2 m); **c** Linera array/Telecom Italia cable on the slope of eastern flank (spatial sampling 2 m); **d** Submarine cable from

Catania harbor down to the INFN submarine observatory (2300 m depth, 25 km from the coast). **e** Three cross-sections showing the probability distribution function of the earthquake location (warm colors indicate higher probability) obtained by inverting interpolated arrival times for the Etna summit and Eastern flank cables only. The black signs represent the location of the cables. The red dot represents the earthquake location provided by the monitoring network of INGV (24 permanent well distributed stations); INGV location: latitude: 506,256 m; longitude 4,176,194 m; depth 4300 m below sea level)



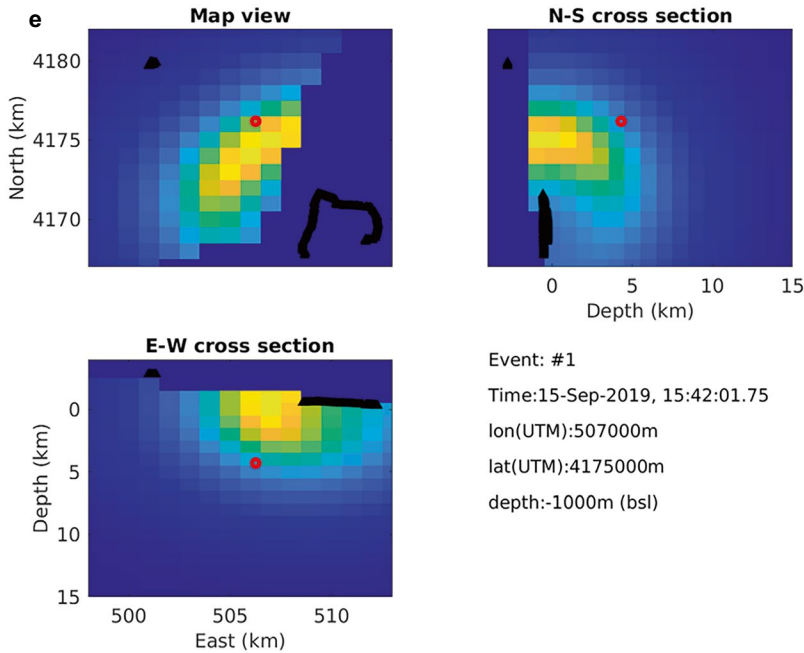


Fig. 17 (continued)

4.2 Challenges, Open Questions and Solutions for Using Distributed Fiber Optic Sensing Technologies

Directionality

A challenge of fiber optic distributed sensing is high anisotropy of sensitivity. The system is mostly insensitive in the direction perpendicular to the fiber. For example, a purely theoretical P-wave (which has a theoretical particle motion in the direction of the wave propagation) will not be detected by a straight fiber deployed in the direction perpendicular to the wave propagation. Conversely a theoretically pure S-wave will be perfectly detected, if it travels perpendicular to the fiber direction. The sensitivity depends on the wave field's orientation with respect to the direction of the fiber (Li et al. 2022). To address this issue, the deployment of cables in various directions has been proposed and tested, such as the PoroTomo array (Feigl et al. 2021). However, processing data from such multi-directional cable with many short linear sections

requires much more complex processing steps and array methods (Johnson and Dudgeon 1993; Van der Ende and Ampuero 2021; Muñoz and Soto 2022) compared to using longer sections of aligned fiber (Currenti et al. 2021; Jousset et al. 2022; Diaz-Meza et al. 2023). Encircling expected epicenters with cables can improve hypocenter determination (e.g., Currenti et al. 2023; Klaasen et al. 2023). Additionally, using multiple cables interrogated independently can lead to even more accurate location determinations, as shown in Fig. 17. Depending on the frequency aimed at (0.1 to 100 Hz on volcanoes), an ideal network could be a triangle, a spiral or star-like deployment of ~1 km aperture.

Coupling

Several options exist to deploy the cable in boreholes. Cementing the fiber optic cable behind casing generally ensures better coupling than using wireline cables deployed temporarily in the borehole (Cox et al. 2012). At volcanoes, due to limited number of boreholes, cables at the surface is likely the sole option, which is

also more cost-effective. The reliability of strain measurements depends heavily on the coupling of the cable with the surrounding media. When the cable is bonded to a structure, coupling is less an issue. However, when it is placed in sediment, coupling depends on the yield stress at the cable-soil interface. In laboratory experiments cables placed in sediment remained well-coupled at small displacements (<15 mm, Wu et al. 2020). However, with increasing strain, the response becomes non-linear and the cable eventually decouples from the soil (Zhang et al. 2016; Viens et al. 2022). The transfer of strain from the ground to the sensing elements in the fiber has been theoretically analyzed (Reinsch et al. 2017). Diaz-Meza et al. (2023) also demonstrated that the cable's structure also affects the records. Further research is necessary to better understand cable coupling and determine if and how anchors could be used to improve it. Modelling tools, such as the one developed by Celli et al. (2024) will help in this respect.

Data management and processing: storage and big data

One of the major challenges of DFOS for real-time applications is the significant amount of data they generate. For instance, Jousset et al. (2022) recorded 12 terabytes of data per week by sampling a 1.5 km long fiber every 4 m for 15 days, albeit not continuously. Similarly, Flovenz et al. (2022) recorded 9 terabytes of data per week (250 terabytes in total) of DDSS fiber optic records by sampling a 21 km long fiber every 4 m for 7 months, continuously. Down-sampling the data either spatially or temporally may be suggested, but this would result in a loss of information, both spatially and temporally. This hinders the significant advantages of these new tools. Quinteros et al. (2021) proposed a solution for storing and sharing data with researchers that do not have access to interrogators. However, the continuous management of the data and the extraction of valuable information for optimal monitoring still need to be defined. The rise in data streams from fiber optic sensing necessitates intelligent data

processing (Arrowsmith et al. 2021). Currently, conversion and pre-processing tools and software are currently being developed (Isken et al. 2021; Quinteros 2021; Spica et al. 2023), but more advanced tools are needed. Machine learning and artificial intelligence approaches could be highly advantageous (Tejedor et al. 2017). Techniques such as neural network approaches (Linville et al. 2019; Wu et al. 2021) are also being targeted. Liehr et al. (2019) proposed the use of artificial neural networks for raw measurement data interpolation and signal shift computation for reducing data analysis time. They demonstrated the benefits of this approach in making the WS-COTDR method usable for real-time applications using telecom dark fiber. As DDSS signals can be presented as 2D or 3D images, it is appropriate to use image processing techniques (Szegedy et al. 2015; Soto et al. 2016; Martins et al. 2019). Machine learning has been successfully applied to detect Very Long Period volcanic events on DDSS records at Vulcano island (Currenti et al. 2023).

Improving the sensitivity and saturation mitigation

The signal to noise ratio of DFOS measurements can be enhanced by stacking records from several parallel fibers of the same cable. This can be achieved by connecting the end of one fiber with another fiber in the same cable resulting in a loop that covers the same geographical location twice. This allows the same locations to be measured twice by simply prolonging the fiber. This technique is feasible for short cables, as DDSS can provide reasonably accurate measurements up to more than 20–30 km in a single fiber. This approach enables stacking of the records (Zwartjes and Mateeva 2015) and enhance accuracy, positioning DDSS as a serious competitor to conventional seismometers. However, signal quality becomes less accurate as the interrogated cable lengthens, creating a trade-off (Diaz-Meza et al. 2023). Fiber technologies have been mainly focused on the ability to measure weak signals. However, in some cases, large strain or strain rate may occur,

such as during earthquakes or explosions, and this can cause the recorded signal to saturate. Saturation occurs when the strain rate exceeds the interferometric ability of the interrogator, resulting in a skip in the optical phase. In practice, it is possible to correct for the phase skip and recover strain rates exceeding the theoretical limit allowed by the interrogator, as long as the strain/strain rate is not too large, and the interrogator is properly set up (Diaz-Meza et al. 2023).

Fibers (helicoidal and engineered fibers)

Zhi et al. (2003) conducted a detailed investigation into the effects of fiber structure on Rayleigh scattering. Lumens et al. (2013) attempted to overcome the directionality limitation by designing dedicated cables, such as helicoidal fiber (Kushinov 2016), which comprises fibers built in a helical shape along the cable. The aim is to probe the strain field in all directions, and potentially overcome the drawback of linear fibers. For instance, Hornman et al. (2013) tested helicoidal cable with the aim of measuring its broad-side sensitivity. They compared the record obtained from the cable with that obtained from 3C geophones. The results indicate that the cable is indeed sensitive in all directions, although the extend of the sensitivity improvement still needs to be proven. However, some experiments have shown that the signal is less accurate when using the helicoidal cable, than when using linear fibers (Bellefleur et al. 2020; Hendi et al. 2023). Another method to enhance the sensitivity is to modify the fiber's structure by incorporating permanent structure modifications of periodic index variations along its length. This allows for optimal light transmission with a specific gauge length, resulting in purposeful enhancement of the backscattered light and in increased sensitivity (Diaz-Meza et al. 2023).

Interrogators

Many recording systems have been proposed and tested in particular for Distributed Fiber Optic Sensing including new generation of DDSS interrogators and smaller instruments with less power consumption. The current consumption of DDSS interrogators is around 200 W (Peng and Cao 2016; Feng et al. 2018; Hartog et al. 2018a, b; Richter et al. 2019). Discoveries at the quantum level (Cohen et al. 2015; Favero 2015) suggest that even very small vibration levels can be detected. Measuring the micro-mechanical properties of biomaterials through nano-indentation is a common technique (Mattei et al. 2017). In the field of volcanology, an ideal interrogator should be capable of simultaneously measuring temperature and strain using the three scattering types: Rayleigh scattering for high-frequency strain sensing (0.1–200 Hz), Brillouin scattering for the ultra-low static strain (DC to minute), and Raman scattering for temperature signals with <0.05-degree resolution. The latter can be used to correct the temperature effect of other scattering processes. The ideal system should be capable of detecting nanostrain signals over a wide frequency range, with high resolution and over a long distance. Currently, such an interrogator does not exist.

5 Conclusions and Perspectives

This chapter presented an introduction to the applications of fiber optic technologies in measuring temperature and the ground motion for volcano research and monitoring across a wide frequency range. Fiber optic methodologies encompass a broad range of instrumentation and techniques. Recent advancements in electronics and optics have led to the development of new instruments that utilize fiber optic principles,

such as Fabry–Perot interferometry, Sagnac effect, and light scattering processes in glass. These instruments have become commercially increasingly affordable in the recent years.

We have illustrated the significant benefits of fiber optic sensing for volcanologists, providing increased spatial resolution and accuracy in probing volcanoes. This leads to new insights on structural features and volcanic processes, allowing for a more complete characterization of the volcano's subsurface structure and a better quantification of processes and seismic wave field. Fiber optic technologies enable a novel approach to monitoring the seismic wave fields and volcanic activity in conjunction with other observation sensors, such as infrasound and geochemistry.

We have discussed advantages and limitations of the methods. The ease of deployment and options provided in remote, steep or space-limited areas are advantages of rotation sensors. Rotation is directly measured and complements the understanding of the wave field. In complex environments it is possible to assess the composition of the seismic wave field and its changes directly. New methodologies such as the ones proposed by Gautier et al. (2022) may be useful in the future for more accurate measurements of rotation. DFOS has considerable advantages over observations with a single point sensor due to the high number of measurements. However, DFOS measurements may present higher instrumental noise. Calibration of DFOS is challenging due to the high spatial variability of coupling to the ground all along the fiber. Although DFOS has only one component measurement, proper array design and dense spatial resolution and temporal sampling provide additional and redundant information. Conventional processing methods in seismology need to be adapted for fiber optic records. For instance, the application of ambient noise processing (Brennguier et al. 2008) is challenging for fiber records due to the high sensitivity of DFOS to local structures. Additionally, research is underway to access the full strain tensor, including all six strain components, using fiber optic methods.

It is worth noting that many volcanoes do not have pre-existing optical fibers, and a significant initial investment seems necessary. In this context, we provide a rough cost estimation for a typical campaign. Let's record a fiber of 2500 channels (15 km, 4 m spatial sampling) for 10 days. The rental cost for an interrogator was 100,000 € (100 €/channel) in 2015 and 10,000 € (10 €/channel) in 2018. Interrogator costs are expected to be around 100,000 € (in 2023), and the cost of a standard cable is estimated to be ranging 1–10 €/m (150,000 € for 15 km for the higher end). Assuming a cost of 1000 € (lower end of cost) for a virtual broadband seismometer with only 1 component only. Deploying 2500 broadband stations along the fiber, this would cost 2,500,000 €, excluding deployment costs. Even with the investment required for purchasing and deploying the cable by digging a trench, the overall cost of the fiber optic approach is significantly lower. Distributed fiber optic sensing offers benefits such as little maintenance, energy and time savings, and the ability to collect dense, accurate and detailed data. For example, the cable deployed at the summit of Etna volcano in the summer 2019 (Currenti et al. 2021) remained unused and with no maintenance for 4 years due to Covid-19 pandemic. In the summer 2023, it became possible to reconnect an interrogator to the fiber. In less than one hour the acquisition system was set up transforming the cable in hundreds of sensors able to record small volcanic events similar to those observed in 2018 (Jousset et al. 2022). This was achieved using four fiber instances, each with 750 channels (Diaz-Meza et al. 2023).

Farghal et al. (2022) discuss the potential of DDSS for early earthquake detection applications. Their conclusions can be transferred and adapted for volcano hazard assessment and improved monitoring, leading to more certain and timely alerts. One strategy is to combine multiple types of instruments to perform joint inversions for hypocenters, source mechanisms and structural features using data from seismometers, rotational sensors and fiber optic interrogators. A detailed plan for combining these

sensor types has yet to be established, building on initial attempts (e.g., Flovenz et al. 2022; Obermann et al. 2022) and exploring new processing algorithms using machine learning and artificial intelligence (Wu et al. 2021; Trainor-Guitton et al. 2022).

Following the onset of the volcanic crisis at Vulcano Island in September 2021, Currenti et al. (2023) demonstrated that a rapid response to a volcanic crisis can be achieved using existing telecom infrastructures. Collaboration between institutions and private companies with available infrastructures, such as telecom companies, is essential and requires preparedness before the crisis begins. Discussions and agreements with the telecom providers at the Sicilian volcanoes over the last years were preparatory to rapidly access the fiber optic network and perform DDSS measurements at Vulcano Island during the crisis (Krawczyk et al. 2020; Napoli et al. 2020). Such preliminary steps are essential for any successful crisis management.

Therefore, we are optimistic and confident that the development of fiber optic technologies on volcanoes will provide additional understanding of volcanic processes. This will lead to a better description of the internal structure and more accurate anticipation of the volcano behavior prior to and during eruptions resulting in improved volcano monitoring and crisis management.

Acknowledgements We would like to acknowledge the following institutions and funding bodies. In Japan: Fukushima River and National Highway Office, Tohoku Regional Bureau, Ministry of Land, Infrastructure, Transport and Tourism (MLIT). Additionally, we used a red relief image map of Azuma volcano (Japan) provided by the Asia Air Survey, Myanmar Co., and MLIT was used. The Geospatial Information Authority of Japan provided the digital elevation model used in the numerical simulations. We thank the Ministry of Education, Culture, Sports, Science and Technology (MEXT) of Japan for their support under the Observation and Research Program for Prediction of Earthquakes and Volcanic Eruptions and ERI JURP 2020-S-04. We also thank HS Orka, ISOR (Iceland Geosurvey), IMO (Iceland Meteorological Office) for their contributions in Iceland. The fiber optic cables used are managed by INFN-LNS/EMSO (Italy), the FLY-LION3 consortium (Mayotte), Telecom Italia (Italy), Mila (Iceland)

or deployed for specific purposes. FLY-LION3 is a submarine cable owned by a consortium consisting of “SRR, Société Réunionnaise du Radiotéléphone”, “Comores Câbles” and “Orange”. We would like to express our gratitude to Parco dell’Etna and the municipalities (Linguaglossa and Castiglione di Sicilia) for granting us the necessary authorizations to deploy the cable and instruments at Piano delle Concazze. The geophones, broadband seismometers and data logger equipment in Italy and Iceland are from the Geophysical Instrumental Pool of Potsdam (GIPP). The fiber optic interrogators used in this study were funded by various institutions: for Mayotte, they were co-funding by Le Mans University, ESEO (Ecole Supérieure d’Electronique de l’Ouest) and IPGP (Institut de Physique du Globe de Paris) with the support from FEDER (50%), as part of the research regional project of Pays de la Loire (RFI WISE). For Iceland and Italy, they were funded by the GeoForschungZentrum Potsdam and the Helmholtz Association. For Mt Meager and Grímsvötn, they were funded by ETH Zürich; for Laacher See: Fieldwork and data collection at LS were made possible thanks to the Transatlantic Research Partnership, a program of the FACE Foundation, and the French Embassy. C.C. acknowledges support from the F.R.S.-FNRS through the MIS CalderaSounds funding. We acknowledge the Helmholtz Association for funding. The European Union Seventh Framework Programme under the Grant No. 608553 (project IMAGE); Horizon 2020 ERC Advances Grant 786304 (project FOCUS); European Union’s Horizon 2020 Research and Innovation Program for IMPROVE ETN under the grant agreement 858092, for SPIN ITN under the Marie Skłodowska-Curie Grant Agreement Number 955515, for Geo-INQUIRE under the grant agreement 101058518; the GeoForschungZentrum Potsdam and the Helmholtz Association; the IS-FNRS funding (Belgium). The PNRR project “SAMOTHRACE” (Italy). We deeply thank Sascha Liehr (DiGOS GmbH) for sharing his expertise in photonics and reviewing an earlier version of this manuscript. Some figures were created using Generic Mapping Tools (Wessel et al. 2019) and Matplotlib (Hunter 2007). The final version of the manuscript was checked for English using Deep-L.

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